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THESIS

SENSITIVITY ANALYSIS OF NAVY AVIATION READINESS-BASED SPARING MODEL

by

Jason J. Pfaff

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Co-Advisor:	Javier Salmerón
Co-Advisor:	Paul Sanchez
Second Reader:	Kevin Maher

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SENSITIVITY ANALYSIS OF NAVY AVIATION READINESS-BASED SPARING MODEL

Jason J. Pfaff
Lieutenant Commander, United States Navy
B.S., DeVry University, 2004

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Approved by: Dr. Javier Salmerón
Co-Advisor

Dr. Paul Sanchez
Co-Advisor

Kevin Maher, CDR (Ret.), SC, USN
Second Reader

Dr. Patricia Jacobs
Chair, Department of Operations Research

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ABSTRACT

This thesis develops statistical analysis in support of Readiness-Based Sparing (RBS) for U.S. Navy aviation weapon systems. RBS seeks to determine the least-cost allowance list to meet pre-specified operational availability of specifically identified systems. The research shows how RBS products such as the Navy Aviation RBS Model (NAVARM) can be used by leadership and builders to anticipate changes in RBS cost as a function of changes in key inputs. We develop NAVARM Experimental Designs (NED), a computational tool created by applying a state-of-the-art experimental design to the NAVARM model. Statistical analysis of the resulting data identifies the most influential cost factors. Those are, in order of importance, availability goal, unit price, wartime flying hours, maintenance rate to failure, high priority order and ship time, number of aircraft, wholesale delay time, rotable pool factor, intermediate maintenance activity repair time, and mean time to repair. Seventy-five percent of NED predictions are within a 3% or less error of actual values for changes within $\pm 10\%$ to baseline values, and all predictions are within 7%.

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THESIS DISCLAIMER

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the U.S. Department of Defense. The efforts put forth in the research were made to reduce all errors. The results obtained from this research have not been validated or endorsed by the U.S. Department of Defense or the U.S. Navy. The reader should know that applying any methods used in this research for other applications would be at his or her own risk.

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LIST OF ACRONYMS AND ABBREVIATIONS

Ao	Operational Availability (RBS_RDGOAL)
ACIM	Availability Centered Inventory Model
AFB	Air Force Base
ARROWS	Aviation Readiness Requirements Oriented to Weapon Replaceable Assemblies
AVCAL	Aviation Consolidated Allowance List
BCM	Beyond Capability of Maintenance
CV	Aircraft Carrier
DOE	Design of Experiments
EBO	Expected Backorders
EXPWFHRS	Expanded War Flying Hours (EXP_PRG_W)
FHRS	Flying Hours (FLY_HRS)
FMC	Fully Mission Capable
HPOST	High Priority Order and Ship Time (HP_OST)
HST	USS *Harry S. Truman*
IMARPT	Intermediate Maintenance Activity Repair Time (IMA_RPR_TM)
ITAT	I-level Turn-around Time
LPOST	Low Priority Order and Ship Time (LP_OST)
MC	Mission Capable
ME	Multi-echelon
MI	Multi-indenture
MRF	Maintenance Rate to Failure
MTTR	Mean Time to Repair
N421	NAVSUP WSS Analyst Office Code
NAVARM	Navy Aviation RBS Model
NAVSUP WSS	Naval Supply Systems Command Weapons System Support

NED	NAVARM Experimental Designs
NIIN	National Item Identification Number
NOAH	Naval Online Allowance Handling
NOB	Nearly Orthogonal and Nearly Balanced
NUMWS	Number of Aircraft (WS_number)
OAT	One-factor-at-a-Time
OPNAV	Office of the Chief of Naval Operations
OPTEMPO	Operational Tempo
OST	Order and Ship Time
QPA	Quantity Per Application
RBS	Readiness-Based Sparing
RIMAIR	Repairable Integrated Model for Aviation
RMSE	Root Mean Square Error
RPF	Rotable Pool Factor
SA	Sensitivity Analysis
SDBLs	Site Demand Based Levels
SHORCALs	Shore-based Consolidated Allowance Lists
SPO	Service Planning Optimization
SQL	Structured Query Language
UNITPRICE	Unit Price of an Item
VBA	Visual Basic for Applications
WFHRS	Wartime Flying Hours (WAR_FHRS)
WDT	Wholesale Delay Time (WHSL_DELAY)
WS	Weapon Systems

EXECUTIVE SUMMARY

The Naval Supply Systems Command Weapons System Support (NAVSUP WSS) Office Code N421 establishes inventory levels for thousands of items to ensure readiness of aviation weapon systems. Since 1985, Readiness-Based Sparing (RBS) is the concept and mandated method to set these aviation weapon-system inventory levels. (Naval Inventory Control Point, 2008, p. 4) RBS models seek pre-specified levels of operational availability (Ao) for multiple weapon systems at minimum cost. There are several RBS models and tools available to NAVSUP WSS. However, NAVSUP WSS cannot assess the sensitivity of the solution (specifically cost), other than modifying the key inputs and running each individual instance.

In 2016, faculty at the Naval Postgraduate School developed the Navy Aviation RBS Model (NAVARM), a heuristic optimization model for single-site and multi-indentured RBS problems. (Salmerón, 2016) NAVSUP WSS code N421 suggested NPS conduct a formal study of influential factors that affect RBS costs calculated by NAVARM. Since NAVARM is open source, we develop the NAVARM Experimental Designs (NED) tool to assess the influential factors.

The thesis objective is to identify the factors most sensitive to the NAVARM output and find the meta-models that estimate RBS cost with minimal error. To enhance this study, N421 provides us with ten test cases that we can use to make our assessments. The test cases vary across multiple aviation platforms on both coasts. Examples of these platforms are USS *Harry S. Truman* (CVN 75) in Norfolk, Virginia and Marine Aviation Logistics Squadron 11 in San Diego, California.

We integrate a nearly orthogonal and nearly balanced (NOB) mixed design spreadsheet with NAVARM. (Vieira, 2012) NOB provides designs that are "low maximum absolute pairwise correlation and imbalance," thereby constructing fully spread-out and equally balanced values. (Vieira et al., 2013, p. 273) NOB is known to improve the cost estimate precision with less variance. We generate a ±10% scaling value in the NOB spreadsheet and apply it to the baseline values of the following 13 factors to all test cases: expanded war flying hours; quantity per application; intermediate maintenance activity repair time; high priority order and ship time; wholesale delay time; unit price; maintenance rate to failure; rotable pooling factor; flying hours; mean time to repair; number of aircraft; RBS performance goal; and wartime flying hours.

Since NAVARM operates in Visual Basic for Applications (VBA), we develop a set of VBA subroutines that interact with the NAVARM model. This process also captures the simultaneous variations of the 13 factors listed above and merges them with NAVARM RBS cost. We expect that this design of experiments will identify the relationship between factors and the NAVARM RBS cost.

After paring the data from multiple trials, we perform a stepwise regression using the statistical software. We identify the most impactful factors along with the best meta-model for estimating NAVARM RBS cost for each test case. In order of importance, the factors are availability goal, unit price, wartime flying hours, maintenance rate to failure, high priority order and ship time, number of aircraft, wholesale delay time, rotable pool factor, intermediate maintenance activity repair time, and mean time to repair. Major sensitivity assessments are as follows:

1. Meta-model development using stepwise regression indicates that 60% of the models have only main effects (no two-way interactions or quadratic effects).

2. Four test candidate files have a quadratic effect. The test candidate files with the quadratic effect are USS *Bataan* (LHD 5), USS *BonHomme Richard* (LHD 6), USS *Iwo Jima* (LHD 7), and *FMS Denmark*. Although these test candidate files are for sites with rotary wing aircraft parts, we cannot conclude that rotary wing aircraft cause this effect.

3. Exponential and reciprocal transformations of one factor, availability goal, show no improvement to the overall meta-model development for those factors with non-linearity. Both transformations on availability goal cause *R-Square adjusted* to decrease, *Root Mean Square Error* to increase, *F ratio* to decrease, and *t Ratio* to decrease compared to the non-transformed meta-

models. This indicates that the quadratic fits best among the choices of transforming availability goal, vice exponentially or reciprocally.

4. One of the test candidate files, Naval Air Facility *Misawa*, has main effects, no quadratic effects, and one two-way interaction.

5. Both USS *Bataan* (LHD 5) and USS *Iwo Jima* (LHD 7) test candidate files have main effects, one quadratic effect, and one two-way interaction.

6. The NED meta-model predictions have 50% of their predictions within a 0.05% to 2% error range for the USS *Harry S. Truman* (CVN 75) test candidate file. The results of the other nine test candidate files have nearly 75% of their predictions within a 3% or less error, while predicting NAVARM RBS cost. NED allows the user to make estimations of cost for all test cases within 7% of actual.

All test cases except Maritime Aviation Logistic Squadron 11 (MAL) have either goal or unit price as their number one factor. The MAL test case has wartime flying hours as its number one factor with unit price as second and goal as its third. The fact that Marine Corps is operating with less than half its aircraft available suggests that the remaining aircraft are being overused, resulting in greater wear and tear and yielding reduced airworthiness. Since this is based on retrospective data we cannot establish causality, but further investigation is warranted.

Overall, we take a prognostic approach to conducting this research. We develop NED to make predictions from data generated by running thousands of NAVARM simulation trials over ten different aviation locations and platforms. This research furthers the development of the desired tool for NAVSUP WSS Office Code N421. N421 can now use current prediction expressions for the ten given cases when the changes to the existing factors are within ±10%. If the changes exceed ±10%, we can use NED with the new NOB, and analyze the output with any statistical software that includes stepwise regression for updated prediction expressions. However, in its current format, NED cannot accommodate new test cases and/or new factors.

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Finally, I would like to thank NAVSUP WSS for affording me this opportunity to study NAVARM. I enjoyed working with the group and its team. It is my hope and prayer that this tool helps them answer questions and save time while they continue to help shape the fleet in these fiscally constrained times.

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I. INTRODUCTION

There ain't no rules around here! We're trying to accomplish something!

—Thomas Edison,
American inventor

The Naval Supply Systems Command Weapons System Support (NAVSUP WSS) mission "is to provide Navy, Marine Corps, Joint and Allied Forces program and supply support for the weapons systems that keep our naval forces mission ready" (NAVSUP WSS., 2017, Mission, para. 1). The primary focus of NAVSUP WSS Philadelphia is on weapons system and aviation support through Readiness-Based Sparing (RBS). RBS models seek to determine the least-cost allowancing (i.e., establishment of inventory levels) to meet pre-specified operational availability (Ao) for all Weapon Systems (WS). Each of these WS consists of multi-indentured parts in the range of tens of thousands. The Department of Defense has used a number of RBS models since the 1960s (Defense Acquisition University, 2012). These models include the Aviation Readiness Requirements Oriented to Weapon Replaceable Assemblies (ARROWS), the Service Planning Optimization (SPO) models, and Repairable Integrated Model for Aviation (RIMAIR). (Note: ARROWS, SPO, and RIMAIR are not available to the researcher, and are only discussed for informational purposes.) Naval Postgraduate School faculty and students are developing the Navy Aviation RBS Model (NAVARM) to guide NAVSUP WSS allowance setting.

An RBS model consists of multiple key inputs such as: rotable pool factor (RPF), wartime flying hours (WFHRS), Ao goal, Unit Price, high priority order and ship time (HPOST), low priority order and ship time (LPOST), wholesale delay time (WDT), intermediate maintenance activity repair time (IMARPT), maintenance rate to failure (MRF), expanded war flying hours (EXPWFHRS), quantity per application (QPA), number of aircraft (NUMWS), mean time to repair (MTTR), and flying hours (FHRS).

These inputs are used to acquire Aviation Consolidated Allowance List (AVCAL) packages. Input values will vary by the type of allowance package, operational necessity, and supported aircraft. The input values are originated by Navy Enterprise Resource Planning, NAVSUP WSS internal business rules, and fleet maintenance, as well as policy from the Office of the Chief of Naval Operations (OPNAV) (Sax, 2012, pp. 4–7). As a result, NAVSUP WSS can improve efficiency and resource allocation by enriching the understanding of how these multiple inputs affect cost. Prior work on RBS assessment has involved determining the factor influence of the ARROWS model to determine RBS cost by varying one input at a time. The impact of jointly varying inputs has never been previously assessed. This thesis develops, and computationally implements, NAVARM Experimental Designs (NED) in order to provide insight into the question, "What are NAVARM RBS cost's most influential factors?"

A. PROBLEM INTRODUCTION

In February 2017, Defense News reported that nearly two-thirds of the U.S. Navy's F/A-18 Hornet and Super Hornets were grounded due to a shortage of parts at aviation depot level. (Cavas, 2017) The article also stated that 53% of all of the Navy's aircraft were grounded as a result of Continuing Resolution Authority budget constraints, maintenance issues, and long lead times for spare parts. A recent example of this problem, as reported in February of 2017, was a reduction in mission capable spare parts available to the Marine Corps, which resulted in only 439 of their 1,065 aircraft to be airworthy. The Marine Corps had to reduce the number of MV-22 Ospreys from twelve aircraft to six in Africa due to their inability to sustain them in the crisis response task force (Seck, 2017).

Currently, the Operations Analyst Office Code N421 at NAVSUP WSS in Philadelphia, PA, uses "Readiness Suite" to create an AVCAL. Readiness Suite is a computer system that combines many tools into a central location, including SPO, RIMAIR and ARROWS (Sax, 2012, p. 2). In creating AVCALs most of the work is centered on using the SPO software, a commercial, off-the-shelf product. For the purpose of this research, SPO and ARROWS are not used to analyze key factors contributing to RBS output.

NAVSUP WSS Office Code N421 wishes to have a stand-alone organic system like NAVARM that will provide them with more flexibility in building AVCALs for different platforms and sites, and that can be adjusted easily for various Weapon Systems (WS). Even with a tool like NAVARM, the N421 team, to some extent, is unsure about how cost is influenced by the previously mentioned factors (Huff, personal communication, July 12, 2017).

B. SCOPE

This thesis will identify the factors that have the greatest impact on NAVARM RBS cost. Through design of experiments (DOE), we develop meta-models that predict the total AVCAL cost for various aviation sites located ashore and at sea. The research will use NAVARM version 1.31. It will identify NAVARM RBS output (RBS cost) by varying a combination of factors. Separate analyses are performed by site location.

This research is expected to help reduce the N421 production run and analysis time by an amount between two and fifteen hours per week. The research will afford N421 the opportunity to better serve allowance builders in building AVCALs, and answer data calls concerning NAVSUP WSS budget.

In addition, the NED tool is developed and implemented in an environment that allows N421 the opportunity to replicate the analyses presented in this thesis as well as conducting new experimentation by varying the previously mentioned factors. However, as currently implemented, NED does not allow the addition of new factors or test cases from those presented in this study.

C. THESIS OUTLINE

The four remaining chapters of this thesis are organized as follows: Chapter II explores the history and background of RBS and acknowledges previous research completed by personnel who work for NAVSUP WSS Office Code N421. Chapter III provides the methodology required to create the DOE as well as the importance and reasoning behind the Sensitivity Analysis (SA) technique. Chapter IV explores the results of the SA and Regression analysis conducted from the DOE simulated trials. Chapter V provides conclusions, future work, and recommendations.

II. BACKGROUND

> The difficulty lies not so much in developing new ideas as in escaping from old ones.
>
> —John Maynard Keynes,
> British economist

This chapter will expound on the RBS history and its significance within the U.S. Navy. It will present a theoretical view of the NAVARM RBS solution, and the SA accomplished by using the ARROWS model.

A. LITERATURE OVERVIEW

Every military service is in dire need to improve system efficiency, reduce costs, and keep fleet assets like aircraft Fully Mission Capable (FMC). A quick overview of history will show that the RBS approach, both in concept and in practice, can assist the services in achieving that goal. The inventory models that use the RBS concept are not the only models in the U.S. military, but the RBS concept is one that supports all service branches.

1. Air Force Base Field Testing of Inventory Model for Repairable Items

While Sherbrooke (2004, p. 60) was working for the RAND Corporation during the 1960s, he developed and implemented an inventory model for the Air Force known as the VARI-METRIC model. This concept is the basis of the ARROWS, SPO, and NAVARM RBS approaches to establish inventory levels. The concept develops an approach to measure performance of supplying parts by measuring backorders instead of fill rate. Fill rate is a percent measure of demands met as orders are placed (Sherbrooke, 2004, p. 11). For the remainder of this thesis we use the terms “RBS approach,” “RBS model,” or simply “RBS” to refer to VARI-METRIC concept. Sherbrooke initially tested his model at Hamilton Air Force Base (AFB). With the help of computer simulations, he field-tested one tactical aircraft type, which resulted in an increased fill rate from 82.8%

to 91.2%, while reducing total investment cost from $1.84M to $1.45M. Even more significantly, the aircraft reduced its nonoperational rate by 42% (Sherbrooke, 2004, p. 10). Despite this promising result, the VARI-METRIC model was initially criticized because only one aircraft type was tested (Sherbrooke, 2004, p. 10). The Air Force then conducted a major test of the model at George AFB, which included three major aircraft, the F-4C, F-104, and F-106, during two six-month periods (Sherbrooke, 2004, p. 10).

The first six-month period was the "pretest" period. During this period, the Air Force developed a baseline with its current model to compare with the field-testing results of the RBS model. The field testing occurred from March 1, 1965, until August 31, 1966. During both the pretest and field testing period, three aircraft types along with 3,673 repairable items were evaluated, and the results were outstanding. As presented in Figure 1, the RBS model improved performance, and reduced the investment (budget) by nearly half. Sherbrooke and his team also noted that a reduction in *Special levels* (seen in Figure 1) from 167 to 28 was not appropriate for the Air Force to achieve large reductions in stock levels. They also noted that had improvements been under 10%, they would have dismissed the overall test, but it is clearly seen from the summary results presented in Figure 1 that this is not the case (Sherbrooke, 2004, p. 11).

	Pretest	Test	% Change from Pretest
Investment ($M)	13.4	7.3	-46
Fill rate (%)	75	76	1
Special levels	167	28	-83
Aircraft possessed	114	96	-16
Flying hours/month	3621	2264	-37
Sorties/month	2009	1362	-32
Average # of backorders	71	40	-44

Figure 1. George AFB test results during Sept. 1, 1965–Aug. 31, 1966. Source: Sherbrooke (2004).

2. RBS Implementation into Naval Aviation

The RBS inventory model was first implemented and tested for the Air Force in 1966. The Navy did not implement the RBS model until the mid-1980s. The Chief of Naval Operations directed the Navy Supply Systems Command to implement RBS, and directed aviation supply to embrace the concept in 1985 (Naval Inventory Control Point, 2008, p. 4). RBS was first used to develop pack-up kits for the SH-60B light airborne multipurpose system, a program used by the U.S. Navy for anti-submarine warfare. (House, 2000, p. 46) Later, the Operational Analysis Department in Mechanicsburg, PA, was tasked with the development and implementation of the RBS model to create AVCALs for all aviation platforms. The resulting model is known as ARROWS.

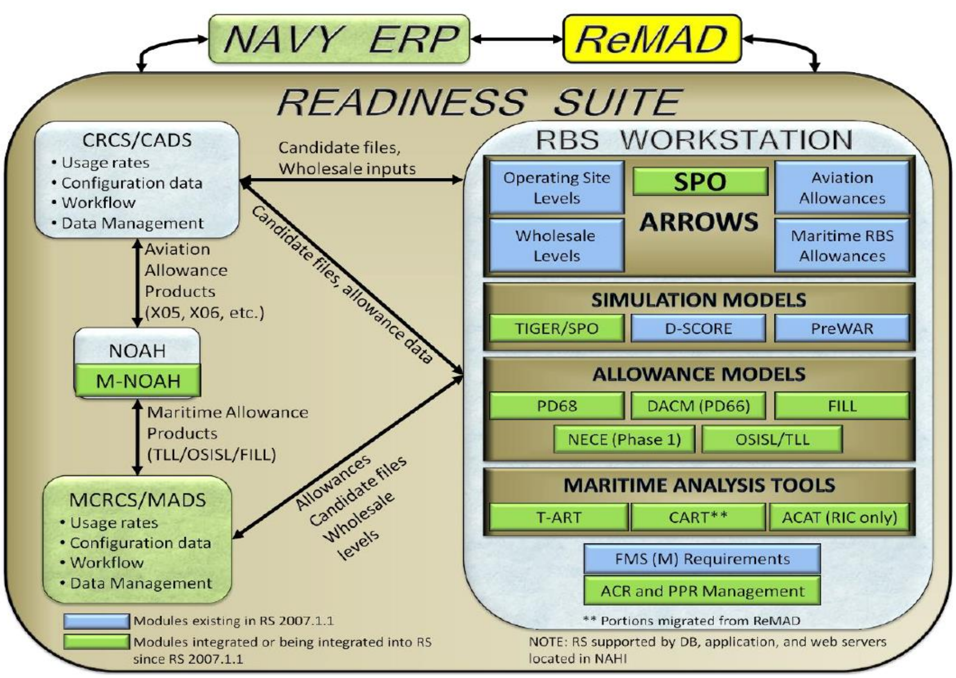
ARROWS testing was accomplished by comparing model predictions with the actual inventory from the Aviation Supply Office for the SH-60B and F14A during the USS *Enterprise* deployment of 1986 (Strauch, 1986, p. ii). The ARROWS model results were compared to the Navy's current model, (called the Availability Centered Inventory Model (ACIM)) and their findings revealed that the ARROWS model maintained a high level of FMC aircraft, reduced AVCAL package cost, and improved overall Ao (Strauch, 1986, p. ii). The analysis team's recommendation was to replace the ACIM with ARROWS, and to start using RBS for future at sea testing. ARROWS would become the Navy RBS approach for aircraft inventory support (Strauch, 1986, p. 26).

In 1993, the U.S. Navy was able to fully integrate the RBS concept on board the USS *America* (CV-66) with the RBS AVCAL. This initiative and analysis reduced the traditional AVCAL dollar investment by $33 million. This was accomplished by increasing the cheaper weapons replaceable units National Item Identification Number (NIIN) range by 24% while decreasing the expensive weapons replaceable units NIIN allowance quantity (House, 2000, p. 46).

3. Readiness Suite

ARROWS continued to dominate as the Navy's RBS model throughout the 1990s, as desktop computers improved in computing power. The overall structure of the ARROWS modeling system migrated from a DOS version to a Windows-based operating system (Sax, 2012, p. 1). Along with ARROWS, the Navy had a multitude of demand-based models and simulators. Instead of cluttering analyst desktops with a slew of tools, the Navy developed the Readiness Suite in 2005. This suite included the web-based Naval Online Allowance Handling (NOAH) system, which improved effectiveness of inputting data, standardized business rules, automated data management, and allowed availability of multiple tools to over 900 users in the Navy organization. (Sax, 2012, p. 1)

As more RBS concepts evolved and multiple tools became available to the analyst, OPNAV authorized ARROWS, SPO, ACIM, and other models to be included in the Readiness Suite, which is depicted in Figure 2 (Chief of Naval Operations, 2011, p. 8. Figure 2 shows more tools and options available through the Readiness Suite than we will discuss. For the purpose of this research, our interest is primarily with the RBS concept for aviation, and those models that are used to plan for allowancing. We bring to the reader's attention the plethora of tools the analyst has available at NAVSUP WSS.



Note: The tools in Readiness Suite are not available to the researcher, and are only mentioned for informational purposes.

Figure 2. Readiness suite components and interactions. Source: Sax (2012).

It is also worth noting that tools like SPO are commercial, off-the-shelf software that will be used in conjunction with other tools like ARROWS, TIGER (a tool similar to ARROWS but used for maritime WS), and ACIM. Sax states in the paper titled, *Aviation Allowancing RBS Overview*, that SPO is a "Flexible model used to compute Site Demand Based Levels (SDBLs), Quarterly Wholesale Levels, Adhoc (Delta) Wholesale Levels, and Readiness Based (RBS) Allowances for AVCALs and large SHORCALs [Shore-based Consolidated Allowance Lists]" (Sax, 2012, p. 3). The pictorial layout of the suite shows that experimental designs could be difficult to investigate (Huff, personal communication, July 12, 2017).

B. THEORETICAL FRAMEWORK

When the Navy adopted the RBS approach, it developed mathematical formulations to calculate the required spares for aircraft AVCALs and SHORCALs. This section explains the RBS theory behind the NAVARM model.

1. RBS Modeling Calculations

Before the basic RBS model calculations are examined in detail, the RBS objective needs to be discussed. According to OPNAV Instruction 4441.5A, the RBS concept is a methodology for

> spares and repair parts allowance determination to ensure that prescribed readiness thresholds and objectives are achieved at the lowest possible cost. Readiness thresholds are expressed as either operational availability (Ao) or full mission capable (FMC) and or mission capable (MC) rates. The term "RBS" applies to single echelon and single indenture systems, as well as their multi-echelon (ME) and multi-indenture (MI) extensions. (Chief of Naval Operations, 2011, p. 1)

Sherbrooke outlines the following assumptions for the VARI-METRIC theory used for RBS:

- All locations and NIINs follow a (s-1, s) inventory policy, where s (the inventory position) is the largest stock level determined from a location. When an order is placed inventory position is reduced by one to meet the demand, which triggers a reorder. Thus, the reorder point is s-1. An order quantity of one is justified by the fact that the NIINs considered are high cost and low demand.

- The expected backorders (EBO) by location are calculated based on a Poisson assumption for the rate of the average pipeline for each NIIN.
- In theory, the overall inventory position s is the number of NIINs on-hand plus the order quantity minus the EBOs.
- When a NIIN is not repairable then a new one is ordered to resupply the location. Also, when the order quantity equals one the inventory position is constant. (Sherbrooke, 2004, pp. 24–25)

The following sub-sections describe the RBS process in sequence.

a. *Average (Resupply and Repair) Pipeline Calculation*

The RBS model will calculate the average pipeline for both the resupplying and the repairing materiel required to keep all fleet assets mission capable. These calculations are presented in Equations (1) and (2):

$$\text{Resupply Pipeline} = \left(\frac{MRF \times QPA \times NUMWS \times WFHRS \times HPOST}{90} \right), \tag{1}$$

$$\text{Repair Pipeline} = \left(\frac{RPF \times QPA \times NUMWS \times WFHRS \times IMARPT}{90} \right), \tag{2}$$

where:

MRF ~ maintenance rate to failure (number of part failures per 100 flying hours that are sent to depot for repair);

QPA ~ quantity per application (number of a particular part per aircraft);

WFHRS ~ wartime flying hours (number of flying hours a squadron fly per quarter divided by 100);

HPOST ~ high priority order and ship time (number of days to transport a part from the stock point to the end user when an MRF failure occurs);

NUMWS~ number of aircraft (number of type aircraft in the squadron);

RPF ~ rotable pooling factor (number of part failures per 100 flying hours that are repaired at the location); and

IMARPT ~ intermediate maintenance activity repair time (number of days between the time of failure and the time ready-for-issue part is installed). (Cardillo, personal communication, December 12, 2016)

The "90" in the denominator of Equations (1) and (2) is a scaling factor to convert days to quarters. Equations (1) and (2) are used to calculate the average number of parts that are within both pipelines. In addition, RBS will find Total Pipeline by summing Resupply and Repair pipelines and this value will be used to calculate the EBOs shown in Equation (3). (Sax, 2012, p. 30)

b. Expected Backorders Calculation

Palm's Theorem is the foundation for inventory theory of repairable NIINs. Sherbrooke (2004, p. 22) states its "…importance is that it enables us to estimate the steady-state probability distribution of the number of units in repair from the probability distribution of the demand process and the mean of the repair time distribution." This implies that knowing just the mean of the repair time distribution, and not the distribution itself, suffices. EBO is calculated as a function of the inventory positions *s* as follows:

$$E[BO;s] = \sum_{x=s+1}^{\infty} (x-s) \frac{e^{-pipeline} \times pipeline^{x}}{x!} \quad . \tag{3}$$

The *x* in the Equation represents the number of failures, whereas the *s* is the inventory position. *Pipeline* is the total pipeline (described above). $E[BO;s]$ calculates expected backorders by NIIN for *candidate files* (i.e., Access database that contains data for multiple factors across many platforms and site locations) developed by the NAVSUP WSS Office Code N421 analyst for each particular site or platform. Naturally, as *s* increases $E[BO;s]$ decreases.

c. Supply Delay Calculation

Once $E[BO;s]$ is calculated, the next step for the RBS approach is to calculate the average amount of time that the system is down (i.e., supply delay) with respect to backorders as follows:

$$\text{Supply Delay} = \frac{E[BO;s]}{(\text{MRF+RPF})\times\text{QPA}\times NUMWS\times\frac{\text{WFHRS}}{2160}}. \qquad (4)$$

The denominator of the Supply Delay Equation (4) is a quarterly unit of measure and is also essential in calculating the system operational availability seen in Equation (5) (Cardillo, personal communication, December 12, 2016). The 2,160 in Equation (4) is the number of hours per quarter.

d. Item Operational Availability Calculation

The calculation in Equation (5) is a key component for the RBS approach and is necessary to determine whether a system is operational based on maintenance and supply requirements (Sherbrooke, 2004, p. 38). NAVSUP defines Ao for a given system as:

$$\text{Ao} = \left(\frac{1}{1+\frac{(\text{Removals}\times\text{MTTR})+\text{E}[\text{BO;s}]}{\text{NUMWS}\times\text{QPA}}}\right)^{\text{QPA}}, \qquad (5)$$

where:

Removals = $(\text{MPR+RPF})\times\text{WFHRS}$ for the item;

NUMWS = number of type aircraft in the squadron; and

MTTR = mean time to repair the WS. (Sax, 2012, p. 31)

According to the OPNAV Instruction 4441.5A, Ao is the best way to measure readiness for Navy parts associated to systems, subsystems and equipment essential to all ship and aircraft missions (Chief of Naval Operations, 2011, p. 3).

e. Cost to Reduce Supply Delay and Cost Effectiveness Ratio Ranked "Shopping List"

Equation (6) shows a critical calculation made by most RBS approaches. The equation is used to build a "Shopping List" by ranking each NIIN's stock level (Cardillo, personal communication, December 12, 2016):

$$\text{Cost Effectiveness Ratio} = \frac{\text{Unit Price}}{\text{Decrease In Supply Delay} \times \left(MRF + RPF\right) \times \dfrac{WFHRS}{2160}}. \qquad (6)$$

The heuristic rule for the RBS-based AVCAL inventory levels calculates the cost effectiveness ratio for different values of *s* for all items, and sorts the ratios in descending order. The shopping list begins with the items and stock levels at the top of the list, until enough items have been added to reach the desired Ao (J. Salmerón, personal communication, May 02, 2017).

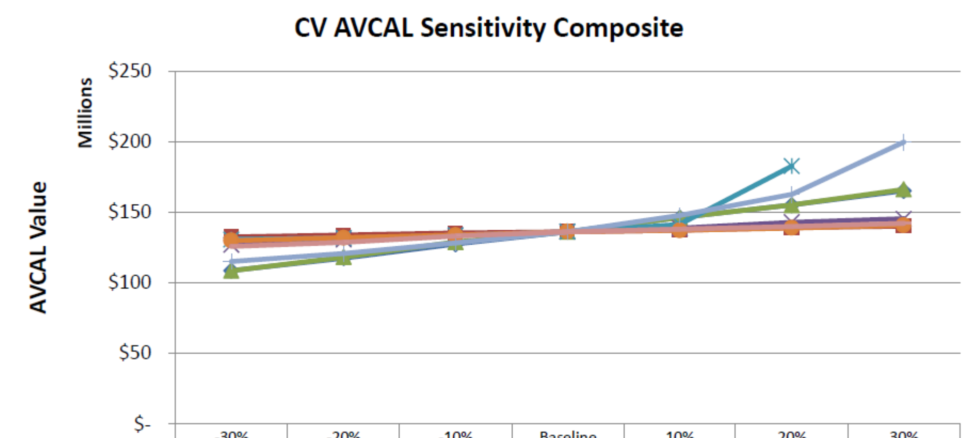
2. NAVARM

For the purpose of this research, NAVARM will be considered a "black box." Furthermore, this research is only interested in the data inputted in, and the direct output from, NAVARM. NAVARM was developed by a team located at the Naval Postgraduate School in 2016 in response to a NAVSUP WSS request for an RBS model that is flexible and transparent in its methodology. NAVARM is adjustable by means of dashboard settings for tolerance, iterations, and maximum solution time. The NAVARM RBS approach applies Equations (1) through (6) with some refinements that we do not detail in this document. NAVARM uses a heuristic optimization to calculate NIIN allowances that minimizes total cost and ensures the target Ao for each WS is satisfied. NAVARM applies to single-site and multi-indentured problems (Salmerón, 2016).

C. ARROWS SENSITIVITY ANALYSIS

In 2012, Sax conducted an SA of the ARROWS RBS model in the NAVSUP WSS Readiness Suite. His SA is different from the one developed in this thesis, but it is significant to consider while performing SA on NAVARM. His analysis was conducted on both RBS and RIMAIR, and the inputs were adjusted from ±10% to ±30%. The inputs that were part of the ARROWS SA are as follows: maintenance rate to failure (MRF), rotable pool factor (RPF), I-level Turn-around Time (ITAT), maintenance cycles (OPTEMPO), FMC, wholesale delay time (WDT), and Beyond Capability of Maintenance (BCM, described below) (Sax, 2012, pp. Appendix I-1-2). His analysis consisted of two SHORCALs, one amphibious class ship and one aircraft carrier. This research will only analyze SA associated with the Aircraft Carrier (CV) AVCAL.

The MRF indicates when a NIIN becomes BCM (i.e., failure rate for parts unable to be repaired at the Organizational (O) or Intermediate (I) Maintenance Levels), while RPF is the rate at which an operating site can repair an I-level failure (Sax, 2012, p. 14). The ITAT is the number of days it takes an O or I-level repairable NIIN to return to the organization's supply system. WDT is a measure of days from the time of requisition until the NIIN is shipped (Sax, 2012, p. 24). Noteworthy in this analysis, the BCM is not an ARROWS model input, but it is used to measure the overall change in output as both MRF and RPF are adjusted. (Sax, 2012, p. Appendix I-1) Next, the Operational Tempo (OPTEMPO) is the number of wartime flying hours for each NIIN of a particular WS (Sax, 2012, p. 23). Lastly, the FMC factor used in the analysis is known as the Operational Availability (Ao) (Sax, 2012, p. 24.) Each WS has its own target Ao, and as these goals are varied, the output is recorded and presented in Figure 3.



	-30%	-20%	-10%	Baseline	10%	20%	30%
Rates	$108,694,549	$117,452,832	$127,409,359	$136,160,442	$146,204,634	$155,139,361	$165,198,922
ITAT	$132,502,929	$133,856,975	$135,193,625	$136,160,442	$137,387,301	$138,983,087	$140,076,678
OPTEMPO	$108,512,260	$118,280,217	$128,912,982	$136,160,442	$146,057,152	$155,190,007	$166,151,987
WDT	$126,891,547	$130,539,441	$133,767,105	$136,160,442	$138,562,607	$142,865,199	$145,421,100
Protection	$130,841,997	$131,705,905	$133,606,735	$136,160,442	$141,219,667	$182,649,100	
Endurance	$129,842,642	$131,924,899	$133,832,683	$136,160,442	$137,111,313	$138,815,878	$140,847,740
FMC	$115,090,356	$120,667,691	$128,253,675	$136,160,442	$147,881,933	$162,578,245	$199,681,267
BCM%	$125,774,282	$128,725,454	$133,149,585	$136,160,442	$137,919,854	$139,975,451	$142,120,152

Adjustment Level

Protection and endurance are not pertinent to this research and are the factors used for RIMAIR. The cell for protection at a 30% increase is blank. It is unclear whether or not this was an infeasible setting because it is not discussed in the document, nor labeled in the image used.

Figure 3. Results from SA of CV AVCAL. Source: Sax (2012).

Figure 3 indicates that the dominant factors are, in order of importance: OPTEMPO, Rates (i.e., combination of MRF and RPF), and Ao. The "dominant factors" are those inputs that AVCAL cost is influenced by. Sax mentions that WDT is the largest driver, but this is not seen in Figure 3 (Sax, 2012, p. Appendix I-3). The discrepancy may be explained because he changed days by percent increments, whereas a better approach would be to adjust WDT along with HPOST by a sequential integer value. As WDT is reduced by one day, it can reduce the value of an AVCAL by 3%, which is very significant. Sax also mentions that high priority order and ship time reacts similarly to WDT because both measure the amount of time in days it takes to get parts into the hands of customers (Sax, 2012, p. Appendix I-4).

Some aspects taken from Sax's SA on CV AVCAL. The factors MRF, RPF, and have a nonlinear relationship with the cost output, whereas the rest of the factors appear to be linear. Sax mentions that there is a relationship between the MRF and RPF given they are both used to calculate the pipeline (Sax, 2012, p. Appendix I-1). However, it is not obvious how those factors interact with each other. In summary, the SA study conducted by Sax appears to use one-factor-at-a-time variation, and clearly suggests CV AVCAL cost factor dominance.

III. DATA REVIEW AND METHODOLOGY

> If you can't fly then run, if you can't run then walk, if you can't walk then crawl, but whatever you do, you have to keep moving forward.
>
> —Martin Luther King Jr.,
> civil rights activist

In Chapter II, we explored the history of the RBS concept and its importance to the U.S. Navy. This chapter will discuss data review, DOE, and SA. These are three essential steps to better identify NAVARM's most influential factors on cost. This research develops NED, a tool that can be used by the NAVSUP WSS analysis team to estimate impacts on project cost given factor variability. (See Figure 4.)

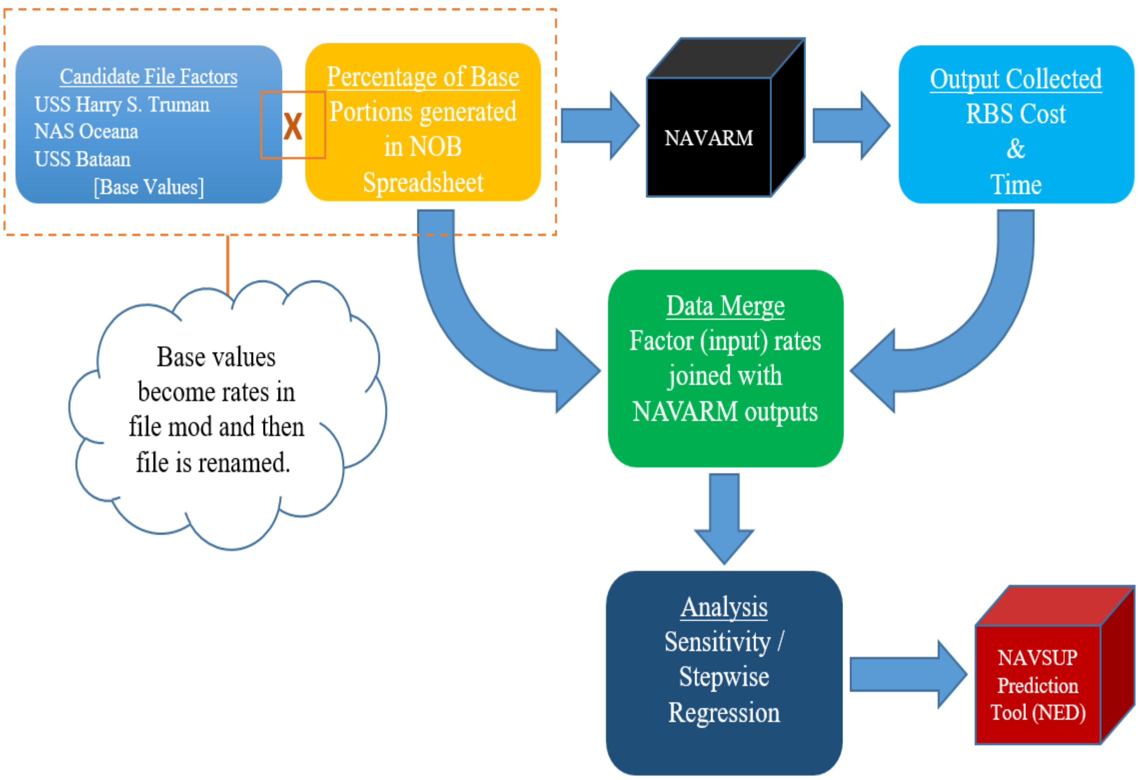


Figure 4. Research design flowchart

Figure 4 lays out the four steps of the methodology, starting in the upper left-hand corner. First, observe the blue block labeled *Candidate File* Factors. The input data is collected from various aviation sites from both Navy and Marine Corps aviation platforms. The key factors are scaled (orange dashed box) by multiplying them with a portion value generated using the Nearly Orthogonal and Nearly Balanced (NOB) mixed design spreadsheet *NOB_Mixed_512DP_V1.xlsx.* (Vieira, 2012) Once factors are modified the Microsoft Access database (used for the baseline scenario provided by NAVSUP) is renamed and saved, therefore maintaining the overall integrity of the original data file.

Second, NAVARM (black box) retrieves the newly named data file and initiates its RBS solving process.

Third, once NAVARM calculates allowances for all NIINs and cost, RBS cost is extracted from the NAVARM RBS worksheet (light blue block) and saved to the spreadsheet containing the NOB factor portions (yellow block). This step matches input and output data (green block).

Fourth, we conduct the statistical analysis to determine the impact of the factors, as well as fitting a regression line to the data to create a meta-model that estimates measured output. Finally, NED (red box in bottom right of Figure 4) is developed for NAVSUP WSS Office Code N421 in an Excel format so that the N421 analyst team can adjust factors and see how they influence RBS cost for each site location. In following the methodology, we conducted a data review so that the correct DOE is applied.

A. DATA REVIEW

Before developing a DOE, this research investigated multiple *candidate files* (i.e., data files used by NAVSUP WSS) and the factors that we, along with NAVSUP WSS, consider likely to be significant. The data review provides a better way of understanding the factors available to the research prior to conducting DOE, and affords us with the opportunity to identify the best method for manipulating data fields in the test candidate files.

1. Factors and Various Candidate Files

The *candidate files* are developed by NAVSUP WSS analyst Office Code N421 in a Microsoft Access database, and those used in this research appear in Table 1.

Table 1. Database candidate files by location

Test Candidate Name	Candidate File	Description / Location
HST	A03242016b-AVCAL-HARRYSTRUMAN-20160420144017.mdb	USS Harry S. Truman (CVN 75) / Norfolk, VA
BON	A06232011c-AVCAL-BONHOMMERICH.mdb	USS BonHomme Richard (LHD 6) / Sasebo, Japan
LEM	A10252012d-REGIONAL-LEMOORE.mdb	Naval Air Station Lemoore / Lemoor, CA
BAT	A11212012-AVCAL-BATAAN.mdb	USS Bataan (LHD 5) / Norfolk, VA
NOR	A04212016b-SASS-NORTHISLAN-20160421145227.mdb	Naval Air Station North Island / North Island, CA
MIS	A06192014a-SHORCAL-MISAWA.mdb	Naval Air Facility Misawa / Misawa, Japan
MAL	A07062011b-CCSP-MALS11.mdb	Marine Aviation Logistics Squadron 11 / San Diego, CA
OCA	A10142014-SHORCAL-OCEANA.mdb	Naval Air Station Oceana / Virginia Beach, VA
DEN	A04202016-FMS-DENMARK-Conf-201604201238001.mdb	Danish Naval Air Squadron / Denmark
IWO	A01112017-AVCAL-IWOJIMA-NAVARM.mdb	USS Iwo Jima (LHD 7) / Mayport, FL

The *candidate files* will be referred to by their test candidate name when discussed in both chapters III and IV. Table 1 describes the platform and location for each candidate file by description and location category. We have a wide range of platforms from shore to sea, as well as aviation data that spans from west to east coast.

To begin, the factor discussion will use the USS *Harry S. Truman* (HST) test candidate name to show its key tables along with each factor's definition. Figure 5 displays the tables ArrowsCandidate, ArrowsParamSW, and ArrowsParamWS, which contain all of the factors we use in this research. We omit additional figures of ArrowsParamSW and ArrowsParamWS tables, but will list those factors that can be found in each.

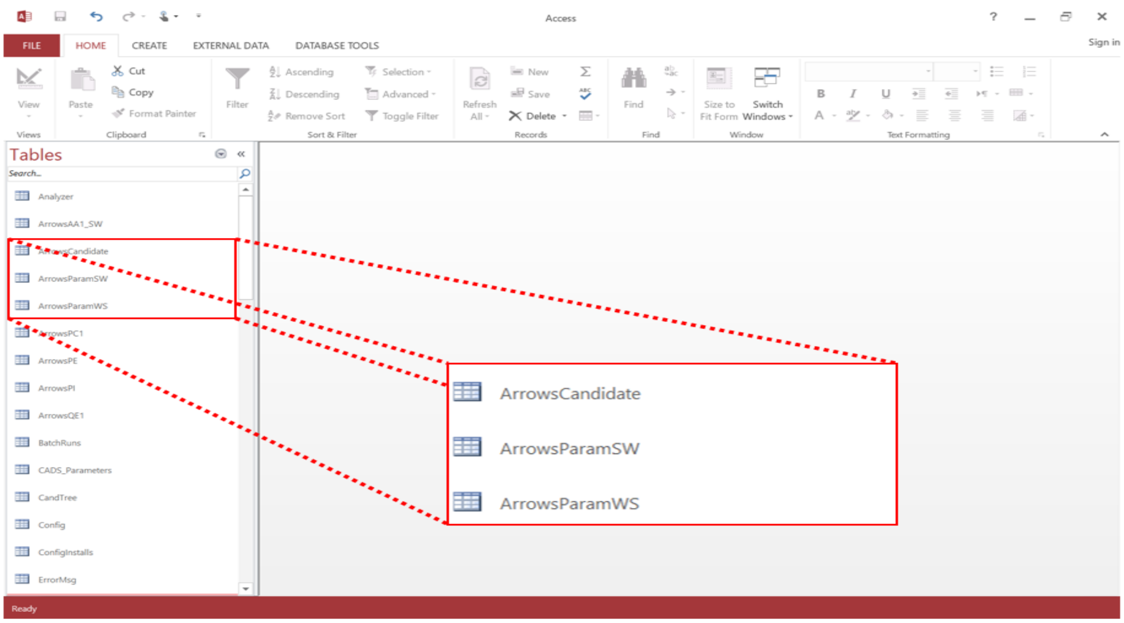
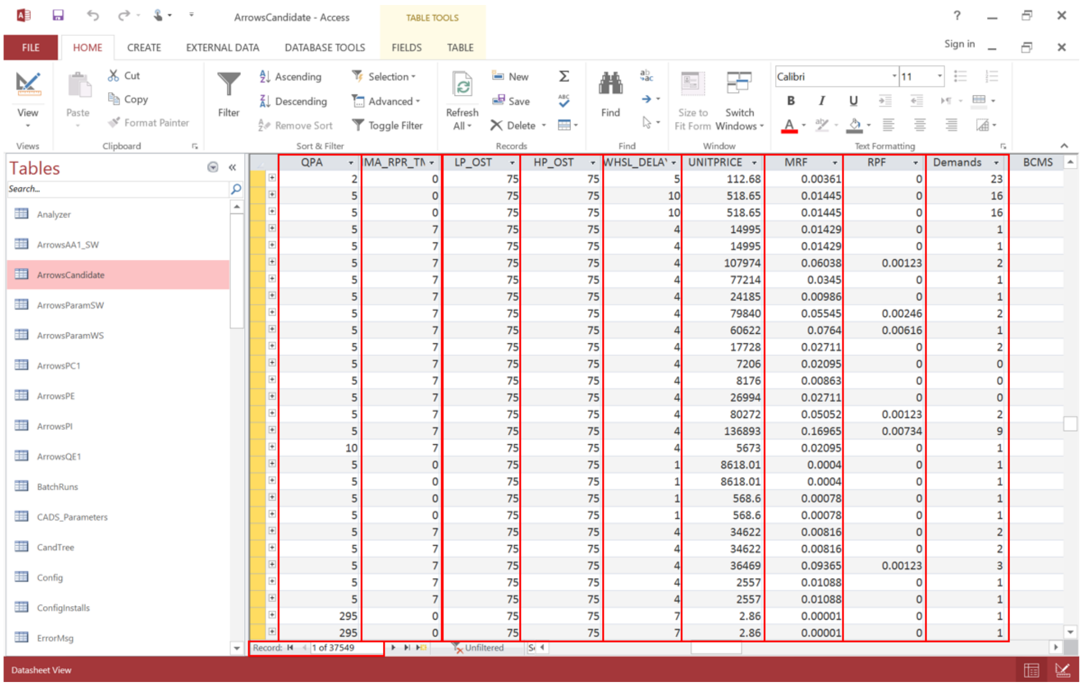


Figure 5. HST test candidate file identifying required tables

The factors located in ArrowsParamSW table are NUMWS, Ao, and WFHRS. ArrowsParamWS contains the MTTR factor only. Figure 6 displays the ArrowsCandidate table, which contains the following factors: QPA, IMA_RPR_TM (also known as IMARPT), LP_OST (also known as LPOST), HP_OST (also known as HPOST), WHSL_DELAY (also known as WDT), UNITPRICE, MRF, and RPF. In addition, it contains two factors not seen in Figure 6: EXP_PRG_W (also known as EXPWFHRS), and FLY_HRS (also known as FHRS). Note: NAVARM also uses the ArrowsParamCS table in its calculations, but that table does not contain any factors for this research.



QPA	MA_RPR_TM	LP_OST	HP_OST	WHSL_DELAY	UNITPRICE	MRF	RPF	Demands	BCMS
2	0	75	75	5	112.68	0.00361	0	23	
5	0	75	75	10	518.65	0.01445	0	16	
5	0	75	75	10	518.65	0.01445	0	16	
5	7	75	75	4	14995	0.01429	0	1	
5	7	75	75	4	14995	0.01429	0	1	
5	7	75	75	4	107974	0.06038	0.00123	2	
5	7	75	75	4	77214	0.0345	0	1	
5	7	75	75	4	24185	0.00986	0	1	
5	7	75	75	4	79840	0.05545	0.00246	2	
5	7	75	75	4	60622	0.0764	0.00616	1	
5	7	75	75	4	17728	0.02711	0	2	
5	7	75	75	4	7206	0.02095	0	0	
5	7	75	75	4	8176	0.00863	0	0	
5	7	75	75	4	26994	0.02711	0	0	
5	7	75	75	4	80272	0.05052	0.00123	2	
5	7	75	75	4	136893	0.16965	0.00734	9	
10	7	75	75	4	5673	0.02095	0	1	
5	0	75	75	1	8618.01	0.0004	0	1	
5	0	75	75	1	8618.01	0.0004	0	1	
5	0	75	75	1	568.6	0.00078	0	1	
5	0	75	75	1	568.6	0.00078	0	1	
5	7	75	75	4	34622	0.00816	0	2	
5	7	75	75	4	34622	0.00816	0	2	
5	7	75	75	4	36469	0.09365	0.00123	3	
5	7	75	75	4	2557	0.01088	0	1	
5	7	75	75	4	2557	0.01088	0	1	
295	0	75	75	7	2.86	0.00001	0	1	
295	0	75	75	7	2.86	0.00001	0	1	

Record: 1 of 37549

Figure 6. HST test candidate file factors in ArrowsCandidate table

For reporting purposes, we also show the number of NIINs in each candidate file. The number of NIINs and number of WS will vary per candidate file. (See Table 2.) Neither one is a factor in our DOE. They are fixed parameters associated with each case. The number of NIINs shown in Table 2 includes RBS-only items.

Table 2. Baseline candidate file specifications

Test Candidate Name	# of RBS NIINs	# of WS Type	A_o Target Range* (%)
HST	11,204	7	59-65
BON	4,145	7	65-82
LEM	77,209	23	46-58
BAT	5,777	7	65-80
NOR	501	1	63
MIS	2,374	3	53-66
MAL	30,181	7	59-75
OCA	35,586	10	46-58
DEN	3,379	1	85
IWO	2,683	6	65-80

*Note: Ao range is for cases with multiple WS.

a. *Factor Definitions*

The next step in completing the data review is to briefly define each factor used to identify NAVARM's output sensitivity. All factors defined below will have their baseline values adjusted within a range of $\pm 10\%$.

- The factor *EXP_PRG_W [expanded war flying hours]* is the quarterly wartime flying hours for a particular item within a certain WS. The expanded war flying hours are determined by dividing a given maintenance cycle rate by 100 for each NIIN in a WS. This value indicates the overall population of the NIIN for that WS. (Oswald et al., 2015, p. 6)

- The factor *QPA [Quantity Per Application]* is the total quantity of each NIIN for each WS. (Oswald et al., 2015, p. 6)

- The factor *IMA_RPT_TM [intermediate maintenance activity repair time]* represents the days necessary to receive a NIIN from organizational maintenance plus the time required for scheduling and repairing the part at the intermediate maintenance facility. This assumes that the essential part to be repaired is available in the system. (Oswald et al., 2015, p. 7)

- Both factors *LP_OST [Low Priority Order and Ship Time] and HP_OST [high priority order and ship time]* are the number of days required to ship a low- and high-priority NIIN, respectively, from the supply system during the requisitioning process (Oswald et al., 2015, p. 8). Both factors are highly correlated; therefore, the low priority factor is dropped from this research. Although the high priority factor appears discrete, for the purpose of this study, we vary it by percentage like all the other factors.

- The factor *WHSL_DELAY [wholesale delay time]* represents the number of days required for the wholesale system to make a *ready-for-issue* part available to satisfy a demand at the customer level. (Oswald et al., 2015, p. 8)

- The factor *UNITPRICE [Unit Price*] represents the price for each NIIN. (Oswald et al., 2015, p. 10)

- The factor *MRF [maintenance rate to failure]* represents the number of failures for each NIIN that cannot be repaired at the site location "per flying hour (or maintenance cycle) per item installed." (Oswald et al., 2015, p. 10)

- The factor *RPF [rotable pooling factor]* denotes the number of part failures that are repaired at each site location per flying hour. (Oswald et al., 2015, p. 10)

- The factor *FLY_HRS [flying hours]* represents the length of use for each part and it can be used to determine a part's rate of failure.

- The factor *MTTR [mean time to repair]* identifies the organization's maintenance hours required to restore a failed WS back to operating. (Oswald et al., 2015, p. 12)

- The factor *WS_number [number of aircraft]* specifies the number of aircraft to support a specific WS. (Oswald et al., 2015, p. 13)

- The factor *RBS_RDGoal [RBS performance goal]* is also known as the goal, which is a percentage used to represent the targeted FMC. (Oswald et al., 2015, p. 14)

- The factor *WAR_FHRS [wartime flying hours]* is the number of "aircraft times the flying hours per quarter per aircraft" in a wartime scenario. (Oswald et al., 2015, p. 15)

b. *Factor Correlations*

We construct a correlation matrix in the statistical software JMP (2017) to identify whether there are any highly correlated factors other than the previously mentioned LP_OST and HP_OST. Observing Figure 7 reveals multiple factors that have a strong positive or negative correlation. For example, the factors QPA and EXP_PRG_W have a correlation of 0.96, RBS_RDGOAL and MTTR have a correlation of 0.81, and RBS_RDGOAL and HP_OST have a correlation of -0.99.

Correlations

	EXP_PRG_W	QPA	IMA_RPR_TM	HP_OST	WHSL_DELAY	UNITPRICE	MRF	RPF	FLY_HRS	MTTR	WS_number	RBS_RDGOAL	WAR_FHRS
EXP_PRG_W	1.0000	0.9583	-0.0263	-0.0140	-0.0244	-0.0068	-0.0077	-0.0025	0.1002	0.0000	0.0000	0.0000	0.0000
QPA	0.9583	1.0000	-0.0450	0.0621	-0.0314	-0.0154	-0.0048	-0.0083	-0.0010	-0.0505	-0.0408	-0.0622	-0.0436
IMA_RPR_TM	-0.0263	-0.0450	1.0000	-0.3775	0.1773	0.2066	0.0032	0.0877	0.0411	0.3237	0.1493	0.3760	0.1681
HP_OST	-0.0140	0.0621	-0.3775	1.0000	-0.1344	-0.1669	0.0132	-0.1027	-0.2590	-0.8178	-0.3894	-0.9996	-0.4288
WHSL_DELAY	-0.0244	-0.0314	0.1773	-0.1344	1.0000	0.0970	-0.0053	0.0334	0.0882	0.1120	0.0391	0.1348	0.0448
UNITPRICE	-0.0068	-0.0154	0.2066	-0.1669	0.0970	1.0000	0.0057	0.1072	0.0365	0.1505	0.0773	0.1666	0.0810
MRF	-0.0077	-0.0048	0.0032	0.0132	-0.0053	0.0057	1.0000	0.0084	-0.0369	-0.0060	-0.0113	-0.0135	-0.0110
RPF	-0.0025	-0.0083	0.0877	-0.1027	0.0334	0.1072	0.0084	1.0000	0.0181	0.1219	0.0311	0.1007	0.0381
FLY_HRS	0.1002	-0.0010	0.0411	-0.2590	0.0882	0.0365	-0.0369	0.0181	1.0000	0.1286	0.4963	0.2670	0.4824
MTTR	0.0000	-0.0505	0.3237	-0.8178	0.1120	0.1505	-0.0060	0.1219	0.1286	1.0000	0.2656	0.8056	0.3237
WS_number	0.0000	-0.0408	0.1493	-0.3894	0.0391	0.0773	-0.0113	0.0311	0.4963	0.2656	1.0000	0.3940	0.9966
RBS_RDGOAL	0.0000	-0.0622	0.3760	-0.9996	0.1348	0.1666	-0.0135	0.1007	0.2670	0.8056	0.3940	1.0000	0.4328
WAR_FHRS	0.0000	-0.0436	0.1681	-0.4288	0.0448	0.0810	-0.0110	0.0381	0.4824	0.3237	0.9966	0.4328	1.0000

Figure 7. Factor correlation matrix for the HST candidate file

The DOE developed for this research seeks to determine the interaction between factors in order to estimate the NAVARM output (specifically cost) as a function of changes in the factors. Specifically, we will estimate AVCAL RBS cost with factors ranging between $\pm 10\%$ of their base value (i.e., from their nominal value in the specific *candidate file* provided by NAVSUP). Section C of this chapter provides a more in-depth discussion of the SA techniques in regards to the NOB DOE.

2. NAVARM Output

The last pieces of the data to be reviewed in this research are the required dependent variables. As each factor (independent variable) defined previously is modified, the RBS cost and time for a NAVARM RBS solution will be collected. Figure 8, features two sections: the left side is the NAVARM Dashboard, and the right side of the figure is the RBS solution worksheet. NED focuses on RBS best cost (incased in the green enclosed box on the left side). We collect the total time to obtain the solution (incased in the yellow enclosed box on the left side) located within the dashboard as well, but we use it for internal purposes to track progress of the DOE trial runs. In the DOE, the dependent variables are matched to corresponding independent variable changes for its specific trial. A complete explanation of how this is accomplished is discussed next.

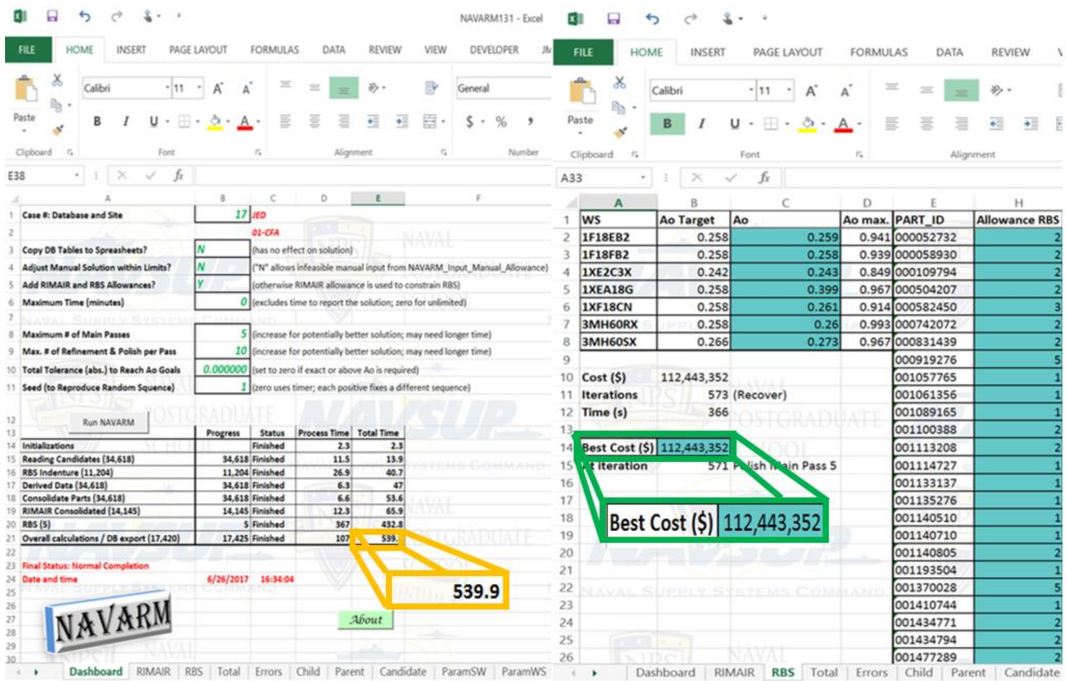


Figure 8. NAVARM split screen of output data collected

B. EXPERIMENTAL DESIGN

Before explaining the DOE, the standard settings of NAVARM will be discussed for each trial. The following discussion identifies the most effective settings in NAVARM in preparation for the DOE simulation trial runs. Parameter settings in NAVARM will remain the same for all trial runs to maintain consistency in the experimental design.

1. NAVARM Configuration

Standard settings for NAVARM trial runs appear in Figure 9, except as noted below. A mix of settings is available. Some are not related to performance. Others are intended to strike a balance between time spent and solution quality (J. Salmerón, personal communication, May 02, 2017).

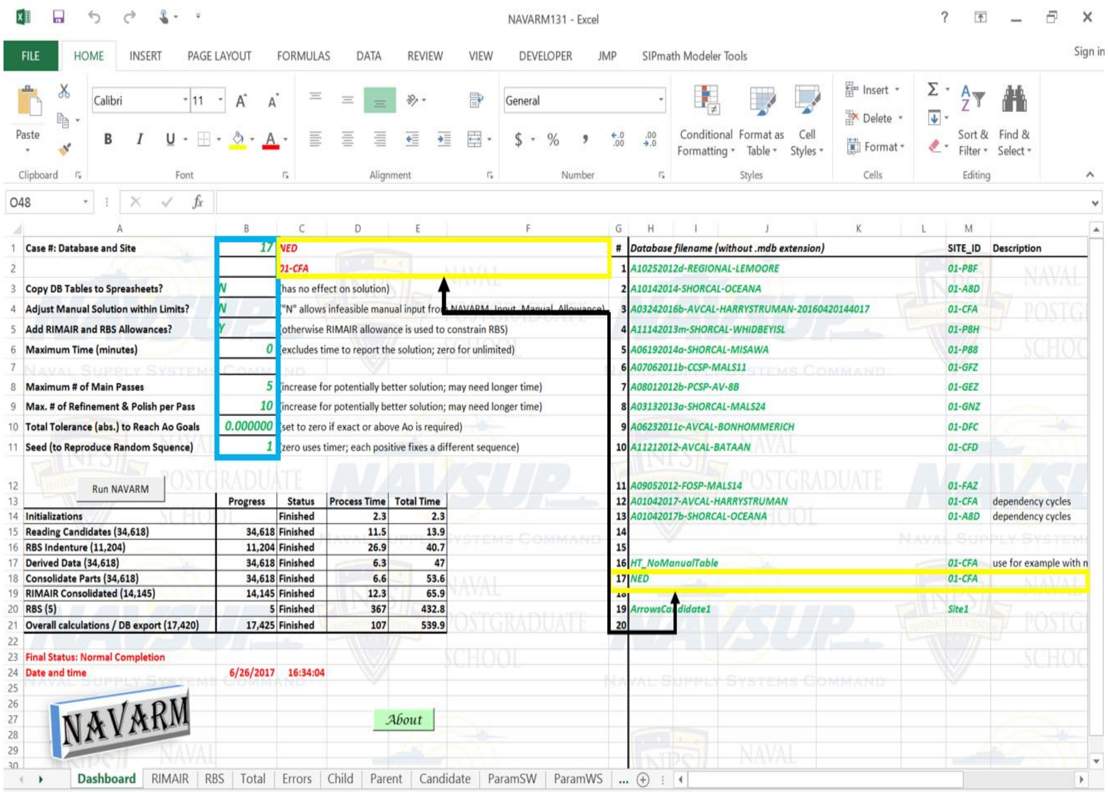


Figure 9. NAVARM Dashboard DOE simulation standard configuration

The focal areas to setup NAVARM for this research appear in the yellow and blue boxes of Figure 9. To start, the yellow boxes are the file names of the candidate file containing the required factors for that specific experiment. In this case, they are named NED, because the original candidate file must remain unchanged for future experimental trials. Outlined with yellow boxes, the candidate file name and its site identification (SITE_ID) are entered in columns H and M under the *Database filename* section of NAVARM Dashboard. Again, we enter the file name and SITE_ID under column C in their second location next to their *Case #* that the user inputs. In this case, the file and SITE_ID are case number 17.

The three settings (shown in the blue box) controlling the length in a NAVARM run are "*Maximum Time (minutes)*," "*Maximum # of Main Passes,*" and "*Max. # of Refinement & Polish per Pass*." The *Maximum Time (minutes)* is the time limit allowed for NAVARM to find a solution, including the time other tasks (such as data preparation, RIMAIR execution, etc.). The special case of zero is used to set an unlimited amount of time, and this is the default choice for NED. The *Maximum # of Main Passes* relates to the number of global iterations for NAVARM to find a solution for the RBS portion of the model. More passes may produce a better solution, but will require more time. The default value for this input is ten, but we changed it to five for NED in order to reduce run time. The *Max. # of Refinement & Polish per Pass* is used to refine the solution, and the input value for this setting is ten. Again, the larger this value is, the longer it will take NAVARM to solve RBS.

Note: Run time may vary by computer. The processor used in this research is an Intel (R) Atom (TM) x7-Z8700 with a 1.6 GHz CPU, and it takes approximately seven to fifteen minutes for NAVARM to produce a solution, depending on the candidate file.

2. Simulation by Visual Basic for Applications

Considering that NAVARM is a tool developed and operated in Microsoft Excel and Visual Basic for Applications (VBA), we develop a set of VBA subroutines that conduct a simulation with the NAVARM model. The following is a list of steps taken to conduct the NAVARM simulation based on the NOB input values:

- The first step is to select suitably scaled values from the NOB spreadsheet, and record those values in a workbook named *NED.xlsm*. The use of the latter spreadsheet will be discussed more in Section C, subparagraph 2 of this chapter.

- Second, a subroutine named *fileNED* in the spreadsheet *NED.xlsm* will access the specified candidate file and change property *Field Size* in Microsoft Access to a “double” (i.e., floating-point that handles most decimal numbers) so that each data field can be manipulated.

- Third, the subroutine, named *LHSscalar,* retrieves the scaled values for all thirteen factors defined above. Structured Query Language (SQL) is used to open the Access database and modify each *field* for each factor with the

NOB value in the workbook named *NED.xlsm*. SQL then closes the database and saves changes made to the factors.

- Fourth, the last subroutine named *runRBS* would open NAVARM, input the candidate file name along with SITE_ID, and then launch NAVARM. Once NAVARM establishes a solution for that trial the subroutine copies the best cost value and the time it takes NAVARM to solve (for internal use only to track the simulation).

- Finally, we wrap the subroutines with a *for loop* that iterates through all of the design points that are defined by the NOB DOE. Once the *for loop* reaches the end of the NOB design, we conduct regression analysis on the data created with new inputs and measurable output (NAVARM RBS cost). Also, with an understanding of the data and process of simulation, the research helps determine the best method of measuring factor dominance as well as regression analysis with the newly developed data.

C. SENSITIVITY ANALYSIS TECHNIQUES

SA is a method for assisting the decision makers in determining future differences while continuing to shape their current policies or business rules. SA requires data that provides us with the ability to investigate the designated dependent and independent variables. We conducted SA upon completing multiple DOEs discussed later in this section using a NOB design that captures changes in AVCAL costs as independent variables vary.

We used the following SA techniques: One-Factor-at-a-Time (OAT) analysis, scatter plots analysis, and regression analysis. Stepwise regression facilitates construction of predictive meta-models, which are the basis of NED.

1. One-Factor-at-a-Time

The OAT is a historical method used to identify main effects. It adjusts one factor at a time while keeping all other factors constant. We use OAT in this thesis to provide a basis for comparison with prior work.

The OAT design is based on Equation (7). The length is determined by the number of variations made to each factor and the number of factors. Each factor is varied up to $\pm 99\%$ in increments of 10%. The final increment is 9% to avoid errors generated if the factors are zero or too large. The *k* in Equation (7) is the number of factors to be examined. (Saltelli et al., 2000, p. 68) The value 20 is the number of levels for each factor.

$$OATdesign = 20k + 1. \qquad (7)$$

As a result, the overall OAT design will consist of 261 trials based on 13 factors.

After completing the OAT trials, *SensitivityRank*, defined in Equation (8), will determine factor ranking:

$$SensitivityRank = \frac{\left|Para_{\max} - Para_{\min}\right|}{Para_{\max}}, \qquad (8)$$

where

$Para_{\max}$ = Maximum value of the measured output (RBS cost)

$Para_{\min}$ = Minimum value of the measured output (RBS cost)

SensitivityRank yields a number between zero and one (Saltelli et al., 2000, p. 176). A value closer to one indicates high output variation, while a value closer to zero indicates the minimal influence on the output. This analysis reflects the interest in NAVARM RBS cost.

2. Design of Experiments

SA alone cannot identify the most influential factors, but a well-crafted DOE can. Saltelli, et al. (2000) state:

> Although there are several differences between physical and simulation experiments, sensitivity analysis is based on the same principles as those underlying DOE. The selection of inputs at which to run a computer code is still an experimental design problem, and statistical ideas for design are helpful (Sacks et al., 1989a). Further, much of the terminology used in SA has originated in a DOE setting. (p. 51)

Sanchez and Wan (2015, p. 1798) discuss why OAT may be ineffective, since it ignores the potential for factor interactions. A well-designed experiment explores combinations of factors that can reveal possible relationships that OAT ignores.

a. Benefits of using Space-filling Nearly Orthogonal and Nearly Balanced

We used NOB design to vary the factors. The NOB methodology is applicable for the following reasons:

- Latin Hypercube sampling is highly flexible and allows the experimenter to span the factor space with a sample size that compares favorably to that of a fractional factorial design. (Sanchez and Wan, 2015, p. 1803)
- According to Vieira, the NOB is a mixed design that is balanced and orthogonal for all factor types and levels. It has "low maximum absolute pairwise correlation and imbalance." (Vieira et al., 2013, p. 273)
- NOB sampling has "good space-filling and orthogonality behavior." (Vieira et al., 2011, p. 3608)

Latin hypercubes provide good estimation of factor effects with low variance (Saltelli et al., 2000, p. 22). Appendix A contains the correlation matrix and scatterplots for the NOB. Note that there is nearly zero correlation among all factors.

b. Scatter Plots

Scatter plots are often used to try to visualize the relationship between the dependent variable and the factors, but the reader should note that they can be misleading in high dimensional cases where projecting to lower dimensions can mask effects. Regression is far more reliable (Saltelli et al., 2008, pp. 17–20). As an example, scatter plots for the HST candidate file are presented in Chapter IV Section B.

c. Regression

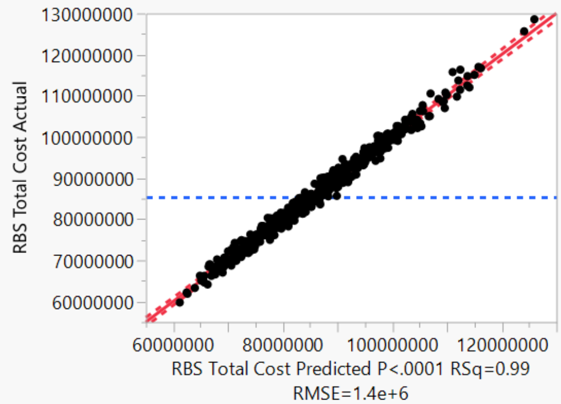
The NOB affords us the ability to assess the influence of each factor on performance measures using regression analysis. Stepwise regression, a well-known technique, efficiently allows us to construct meta-models. Figure 10 shows diagnostic information that can be used to assess the quality of the model fit for the HST test case. After determining which factors are most influential from this assessment, the final step is to generate the prediction formula for NAVARM.

The resulting regression model is presented in Figure 11. In this case, the *Prediction Expression* for HST shows that the meta-model has only main effects when estimating the NAVARM RBS cost. The coefficients for each factor are all positive except the factor WS_number, which shows a negative correlation relationship to RBS cost. We apply this process to the other nine test candidate files using the statistical software JMP (2017).

Response RBS Total Cost

Effect Summary

Actual by Predicted Plot



Summary of Fit

RSquare	0.986296
RSquare Adj	0.985442
Root Mean Square Error	1375272
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	30	6.5478e+16	2.183e+15	1153.976
Error	481	9.0975e+14	1.891e+12	Prob > F
C. Total	511	6.6388e+16		<.0001*

Figure 10. Stepwise regression results example

Prediction Expression

-566966909.9203
+ 2926935.78815754 * HP_OST
+ 32288847.0199892 * WHSL_DELAY
+ 181591141.901322 * UNITPRICE
+ 155763845.856915 * MRF
+ 152125728.399188 * WAR_FHRS
+ -51297727.194505 * WS_number
+ 152646655.673763 * RBS_RDGOAL

Figure 11. Stepwise regression prediction formula

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IV. ANALYSIS

> Statisticians, like artists, have the bad habit of falling in love with their models.
>
> —George E.P. Box,
> British statistician

In Chapter III, we discussed the methodology for developing data using the ten test candidate files. This Chapter analyzes how NAVARM's RBS cost output is sensitive to different factor variations. The regression results are assessed using four statistical measures: *R-Square adjusted*, Root Mean Square Error (*RMSE*), *F ratio*, and *t Ratio.* (Cleary and Levenbach, 1982, pp. 43–51) We only display the meta-model results for HST test candidate file in Section C, subparagraph 1 of this chapter. In Appendix D, we provide the remaining nine test candidate file meta-model results.

A. ONE-FACTOR-AT-A-TIME RESULTS

We experimented with the OAT design for a few of the test candidate files prior to conducting the NOB DOE to see if any factors largely affect NAVARM RBS cost. This method is intended to be informative in observing how sensitive NAVARM RBS cost is to each factor. We conducted OAT design in five of the ten test candidates' files listed in Table 1: HST, MIS, BON, OCA and BAT. The OAT experimentation resulted in a similar conclusion among all site locations. This result only changes one factor at a time without interactions. The sensitivity results (Figure 12) display HST RBS cost as a function of changes to the baseline values.

It is worth noting that the cost of HST allowances appears to increase exponentially as the RBS_RDGOAL (baby blue) factor increases. However, as the factor WS_number (number of aircraft) is reduced there appears to be a negative effect on RBS cost. Additional SA graphs of the four-other site locations are in Appendix B. The graphs capture each factor change as it is increased or decreased from its candidate file baseline value. However, they do not inform us which factors are most influential, nor do they identify interaction effects.

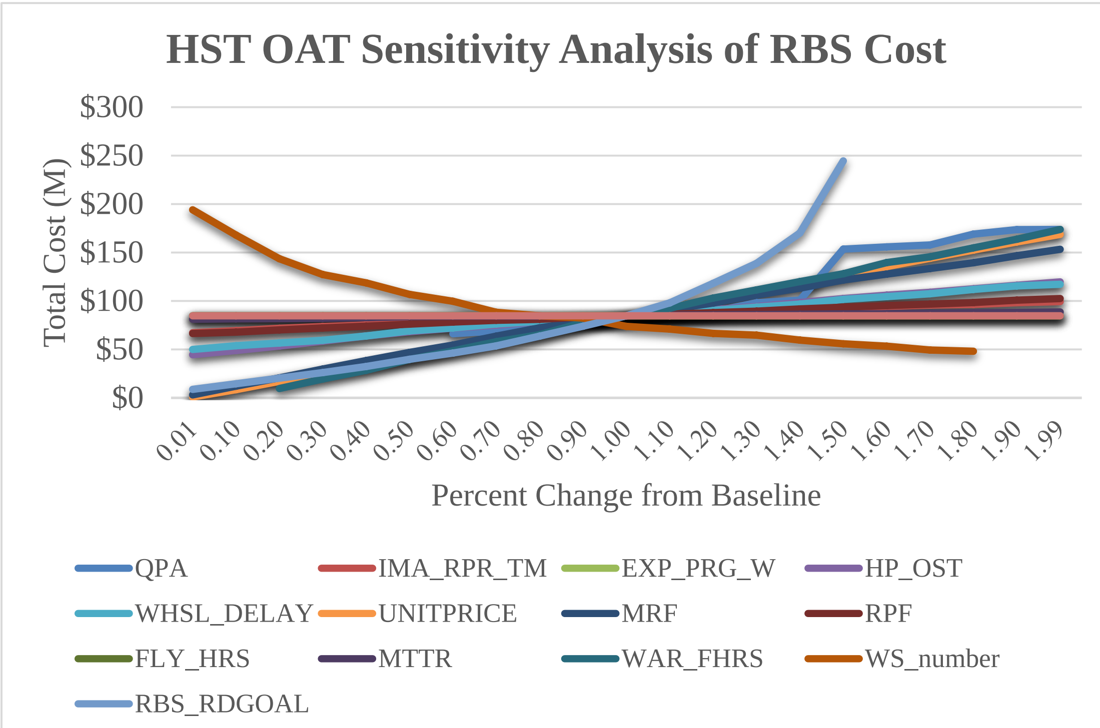
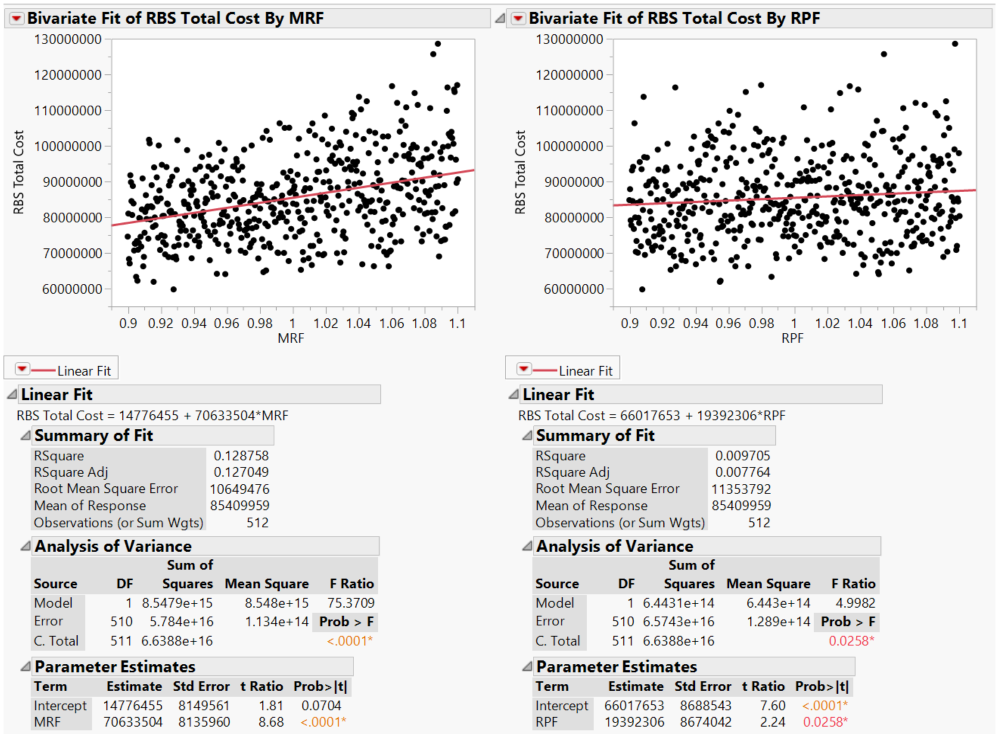


Figure 12. HST OAT SA for RBS cost

B. SCATTER PLOT RESULTS

Like the OAT design, the scatter plots are often used to assess the sensitivity of NAVARM RBS cost as given factors change in value. Two scatter plots, along with fitted lines for the factors MRF and RFP, are shown in Figure 13. The rest of the scatter plots for each factor can be seen in Appendix C. The scatter plots are a visual tool to show how one factor reacts to the output and, in this case, to RBS cost. The formulae created for the one factor *Bivariate Fit* in Figure 13a and Figure 13b are not useful in making predictions for the entire model, but they can provide estimates for individual factor main effects.



a. MRF by RBS cost b. RPF by RBS cost

Figure 13. HST bivariate fit of two factors by RBS cost

C. STEPWISE REGRESSION MODEL RESULTS

OAT is a mediocre design for identifying the factor effects, and scatter plots provide minimal insight on factor effects. Stepwise regression will best identify NAVARM RBS cost sensitivity and provide us a capability in building our best fit meta-models that will make predictions for all factor variations.

1. Meta-model Fit

Finding the meta-model, using the stepwise regression process discussed in Chapter III, is the focus of this section. The HST test candidate file data is used to illustrate the meta-model fitting for the rest of the experiment. Also, the stepwise regression results for NAVARM RBS cost are explained in detail for developing a practically significant meta-model.

Additionally, the nine other test candidate files have been analyzed using the same process as HST. Their statistical summaries are available in this Section under

Subparagraph 2, but their meta-models can be seen in Appendix D. The meta-models are developed by starting with all main, two-way interaction, and quadratic effects. With 13 factors, there are 78 (13 choose 2) two-way interactions plus 26 (13 times 2) main and quadratic effects. The number of potential terms is thus 104.

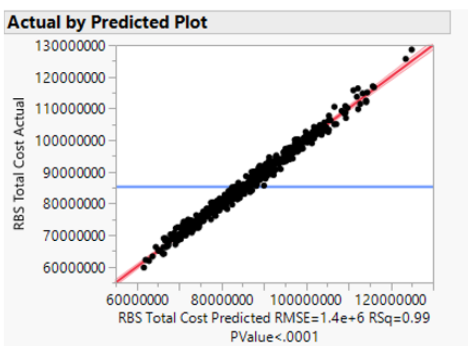
The stepwise regression will assess all terms, and while stepping through them, find those that are statistically significant for the data. In Figure 14, the stepwise function for the HST test candidate file finds only 22 effects out of the 104 that are statistically significant in developing the model. We choose those with a *t Ratio* greater than ten because we deem them "practically significant." Those effects on the lower end (highlighted in red box in Figure 14) have less effect on the outcome, and we judged that estimation power principally lies in those nine main effects.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio		Prob>|t|
RBS_RDGOAL	117207984	1086834	107.84		<.0001*
UNITPRICE	87835620	1088261	80.71		<.0001*
WAR_FHRS	82865685	1091193	75.94		<.0001*
MRF	67261340	1098950	61.21		<.0001*
HP_OST	38242625	1092030	35.02		<.0001*
WS_number	-33407751	1089640	-30.66		<.0001*
WHSL_DELAY	29921528	1086965	27.53		<.0001*
RPF	17503365	1079438	16.22		<.0001*
IMA_RPR_TM	14727843	1083134	13.60		<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	124887896	19274956	6.48		<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	115427067	18698229	6.17		<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	93752538	21140391	4.43		<.0001*
(UNITPRICE-1)*(RPF-1)	66906499	19067511	3.51		0.0005*
(WS_number-1)*(RBS_RDGOAL-1)	-67118307	19257367	-3.49		0.0005*
(UNITPRICE-1)*(MRF-1)	66507190	19195944	3.46		0.0006*
(UNITPRICE-1)*(WAR_FHRS-1)	63308941	19157449	3.30		0.0010*
(HP_OST-1)*(RBS_RDGOAL-1)	60314032	19029434	3.17		0.0016*
(MRF-1)*(RBS_RDGOAL-1)	58942450	18872395	3.12		0.0019*
(HP_OST-1)*(MTTR-1)	-60147377	19668710	-3.06		0.0024*
(IMA_RPR_TM-1)*(WAR_FHRS-1)	54169763	18594104	2.91		0.0037*
(WHSL_DELAY-1)*(WAR_FHRS-1)	52460238	19185454	2.73		0.0065*
MTTR	2770540.7	1083678	2.56		0.0109*

Figure 14. HST stepwise regression results for main, two-way interactions, and quadratic effects.

Figure 15 shows that the reduction in effects from the bounds set on the *t Ratio* is minimal. Figure 15a displays the meta-model with all statistical significant effects selected by stepwise regression. Figure 15b displays a meta-model with only main effects (no two-way interactions or quadratic effects) that have a *t Ratio* greater than ten, as discussed previously. Starting at the top, observing both Figures 15a and 15b, the *Actual by Predicted Plot* shows meta-models that have a tight grouping of data points with a prediction line (red) that passes precisely through the center of the grouping with minimal variation between points, hence the large *R-Squares adjusted*. In fact, both *R-squares adjusted* are nearly the same, the *RMSE* are only slightly different, and the reduced meta-model in Figure 15b has an *F ratio* nearly twice that of the full meta-model in Figure 15a. This reduction in the number terms included in the meta-model does not noticeably reduce the effectiveness of the meta-model itself, based on observed plots and statistical summaries.



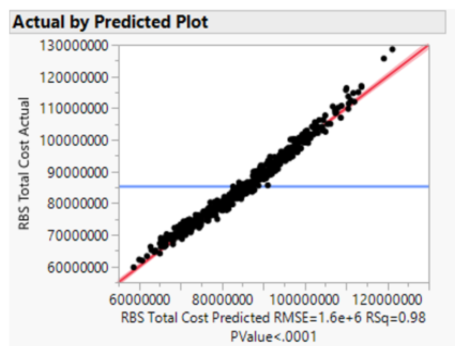
Summary of Fit

RSquare	0.985384
RSquare Adj	0.984727
Root Mean Square Error	1408638
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	22	6.5417e+16	2.974e+15	1498.552
Error	489	9.703e+14	1.984e+12	Prob > F
C. Total	511	6.6388e+16		<.0001*

a. HST Meta-model (Full)



Summary of Fit

RSquare	0.979434
RSquare Adj	0.979065
Root Mean Square Error	1649191
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

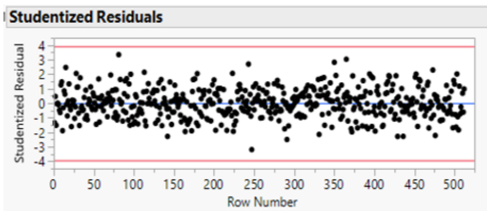
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	6.5022e+16	7.225e+15	2656.306
Error	502	1.3654e+15	2.72e+12	Prob > F
C. Total	511	6.6388e+16		<.0001*

b. HST Meta-model (Reduced)

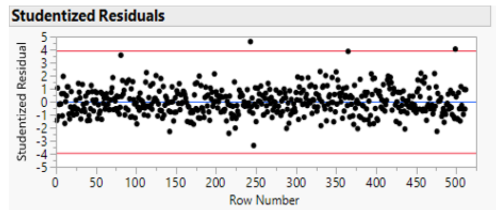
Figure 15. HST meta-models Actual by Predicted with statistical summaries

To identify outliers, *Studentized Residual* plots are displayed for HST NAVARM RBS cost in Figure 16. As a check and balance, we conducted *Studentized Residual* plots for all test candidate file meta-models (full and reduced), and they are available in

Appendix D. In Figures 16a and 16b, the data points appear tightly fit on the centerline (blue horizontal line) leading us to determine that neither meta-model has outliers.



a. HST Meta-model (Full)



b. HST Meta-model (Reduced)

Figure 16. HST meta-models studentized residual plots

For simplicity and practicality, we decided to use the reduced meta-model with the main effects only. The remaining nine test candidate files were developed using the same technique described for the HST test candidate file. While developing the meta-models it is notable that 60% of the models developed have only main effects (no two-way interactions or quadratic effects). However, there are four test candidate files that have a quadratic effect (RBS_RDGOAL × RBS_RDGOAL). The test candidate files that have the RBS_RDGOAL quadratic effect are BAT, BON, IWO, and DEN. The interesting characteristic about these four test candidate files is that they are for sites with rotary wing aircraft parts. However, we cannot conclude that rotary wing aircraft cause this effect.

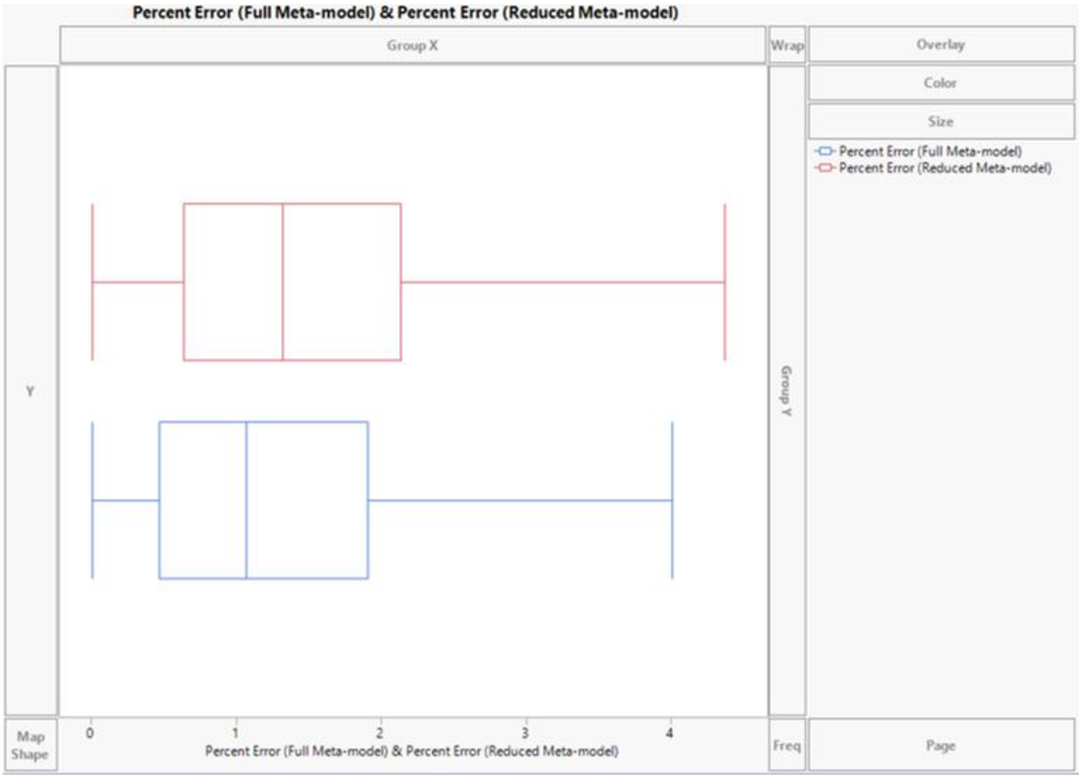
Exponential and reciprocal transformations of the factor RBS_RBGOAL show no improvement to the overall meta-model development for those with non-linearity. In fact, both of those transformations on RBS_RDGOAL cause *R-Square adjusted* to decrease, *RMSE* to increase, *F ratio* to decrease, and *t Ratio* to decrease compared to the non-transformed meta-models, indicating that the quadratic fits best among these choices.

Finally, the test candidate file MIS has main effects, no quadratic effects, and one two-way interaction (WAR_FHRS × RBS_RDGOAL). Also, BAT and IWO test candidate files both have main effects, one quadratic effect (RBS_RDGOAL × RBS_RDGOAL), and one two-way interaction (WAR_FHRS × RBS_RDGOAL).

2. Meta-model Statistics Using Stepwise Regression

To further compare the prediction power between both HST Full and Reduced Meta-models, the percent error for each is displayed in Figure 17 (x-axis in percent). The category Meta-model (Full) includes those models developed using stepwise regression, but with low *t Ratios* remaining. However, the Meta-model (Reduced) comprises the models with *t Ratios* that have an absolute value of ten or greater (low magnitude *t Ratios* removed). The red box plot is the prediction error for the reduced meta-model and the blue box plot represents the prediction errors in the full meta-model. Significantly, both full and reduced meta-models have 50% of their predictions of NAVARM RBS cost within the 0.05% to 2% error range. More importantly, it shows the similarity of both full and reduced meta-models. In addition, the nine other test candidate percent error box plots are available in Appendix E. The results of those nine test candidate percent error box plots display for all cases that nearly 75% of their predictions of NAVARM RBS cost are less than 3% of error.

The meta-model statistics are available in Table 3 for NAVARM RBS cost. The table contains the statistical measures of the meta-models available in Appendix D. The significance of Table 3 is to illustrate that the removal of the low end *t Ratio* factor does not drastically change the performance of the meta-model. In fact, there are some test candidates that experience minor changes in *R-square adjusted* and *RMSE*, but nearly double in value for the *F Ratio* as effects are removed from the meta-models.



Note: The red box plot is HST reduced meta-model. The blue box plot is the full meta-model. The x-axis is percent error calculated by the difference between actual and estimated, divided by actual.

Figure 17. HST RBS cost prediction error for full and reduced meta-models

Table 3. Test candidate meta-model statistics for NAVARM RBS cost

RBS Total Cost Meta-model Statistical Table						
	Meta-model (Full)			Meta-model (Reduced)		
	Rsquare Adjusted	RMSE	F Ratio	Rsquare Adjusted	RMSE	F Ratio
HST	0.98	1408638	1499	0.98	1649191	2656
LEM	0.98	1092954	901	0.96	1395977	1631
BAT	0.97	3463740	1003	0.96	4558055	1199
BON	0.98	1850437	1300	0.97	2432405	2066
NOR	0.93	421271	631	0.93	441221	1256
MAL	0.97	3628082	626	0.95	4492968	1159
IWO	0.97	3130217	679	0.95	3977324	1031
MIS	0.98	724969	1181	0.97	897656	2287
OCA	0.98	1532184	725	0.96	1895954	1505
DEN	0.98	1638973	1379	0.98	1821543	2498

3. Influential Factors Results

Finally, we provide the NAVARM RBS cost factor influence ranking. In Table 4, a list of factors from left to right is displayed for each candidate file. The list is gathered from their meta-model developed in stepwise regression. The ranking of the factors is 1 to 13, representing largest to smallest magnitudes for the *t Ratios*, respectively. Factors in *red text* are the main effects that are statistically significant, but have been removed from the model due to the *t Ratio* being smaller than ten (i.e., not practically significant).

Additionally, we count how many times each practically significant factor appears in all test problems. We find that the overall most influential factors on cost are (in order of importance): goal, Unit Price, wartime flying hours, maintenance rate to failure, high priority order and ship time, number of aircraft, wholesale delay time, rotable pool factor, intermediate maintenance activity repair time, and mean time to repair.

All the test cases, except MAL, have either goal or unit priceas their number one factor. The MAL test case has wartime flying hours as its number one factor with unit priceas second, and goal as its third. As mentioned in Chapter I, Section A, the Marine Corps is operating with less than half their aircraft available. This suggests that the remaining aircraft are being overused, resulting in greater wear and tear and yielding reduced airworthiness. Since this is based on retrospective data we cannot establish causality, but further investigation seems indicated.

Table 4. NAVARM’s RBS cost influence to factors by t ratio ranking

RBS Total Cost Factor Influence by t Ratio Ranking from Meta-models													
	1	2	3	4	5	6	7	8	9	10	11	12	13
HST	RBS_RDGOAL	UNITPRICE	WAR_FHRS	MRF	HP_OST	WS_number	WHSL_DELAY	RPF	IMA_RPR_TM	MTTR	-	-	-
LEM	RBS_RDGOAL	WAR_FHRS	UNITPRICE	RPF	IMA_RPR_TM	MRF	HP_OST	WS_number	WHSL_DELAY	QPA	-	-	-
BAT	RBS_RDGOAL	UNITPRICE	WAR_FHRS	MRF	HP_OST	WS_number	MTTR	RPF	QPA	WHSL_DELAY	IMA_RPR_TM	-	-
BON	RBS_RDGOAL	UNITPRICE	WAR_FHRS	MRF	WHSL_DELAY	HP_OST	MTTR	WS_number	RPF	IMA_RPR_TM	-	-	-
NOR	UNITPRICE	RBS_RDGOAL	WAR_FHRS	MRF	HP_OST	QPA	-	-	-	-	-	-	-
MAL	WAR_FHRS	UNITPRICE	RBS_RDGOAL	MRF	RPF	IMA_RPR_TM	WS_number	WHSL_DELAY	HP_OST	MTTR	-	-	-
IWO	RBS_RDGOAL	UNITPRICE	WAR_FHRS	MRF	WS_number	HP_OST	WHSL_DELAY	MTTR	RPF	QPA	-	-	-
MIS	RBS_RDGOAL	UNITPRICE	MRF	WAR_FHRS	HP_OST	WS_number	WHSL_DELAY	MTTR	RPF	IMA_RPR_TM	QPA	-	-
OCA	UNITPRICE	RBS_RDGOAL	WAR_FHRS	MRF	HP_OST	IMA_RPR_TM	WHSL_DELAY	RPF	WS_number	-	-	-	-
DEN	RBS_RDGOAL	UNITPRICE	WAR_FHRS	MRF	WHSL_DELAY	HP_OST	WS_number	-	-	-	-	-	-

D. NAVSUP TOOL

After identifying the NAVARM output sensitivities and developing the meta-models, an estimation tool was developed for NAVSUP WSS in Excel using VBA. The tool affords NAVSUP WSS, Office Code N421, the ability to make adjustments to multiple factors simultaneously, and see how that affects NAVARM RBS cost. Implementation of NED will aid N421 in training and planning, and will improve their overall understanding of factors that affect RBS sensitivity.

V. CONCLUSION

We demonstrate that the most influential factors to NAVARM RBS cost are availability goal, Unit Price, wartime flying hours, maintenance rate to failure, high priority order and ship time, number of aircraft, wholesale delay time, rotable pool factor, intermediate maintenance activity repair time, and mean time to repair.

Prior to this research, Sax (2012, Appendix I-4) discovered that wholesale delay time and high priority order and ship time were the drivers behind the RBS model. This thesis found that both factors influence the output, but they are not the most influential. We suggest that future work consider a DOE that varies both factors as continuous integers rather than scaling from the baseline value.

In conducting the OAT design and assessing the scatter plots analysis, we note that these historical methods cannot reliably determine which factors are most influential, nor can they provide accurate estimates of RBS cost. Stepwise regression, by contrast, succeeds at both. Our findings are that 60% of the models have only main effects (no two-way interactions or quadratic effects). However, four test candidate files have a quadratic effect (RBS_RDGOAL × RBS_RDGOAL). The test candidate files with the RBS_RDGOAL quadratic effect are USS *Bataan* (LHD 5), USS *BonHomme Richard* (LHD 6), USS *Iwo Jima* (LHD 7), and *FMS Denmark*. These four test candidate files are for sites with rotary wing aircraft parts, but we cannot conclude that rotary wing aircraft cause this effect. The MAL test case has unique factor ranking, and suggests further study in order to explain these differences.

NED is developed as a predictive tool for NAVARM RBS cost based on the stepwise regression models for the ten test cases, and produces predictions of cost when factors vary within the scaled range. The NED meta-model for the USS *Harry S. Truman* has 50% of its predictions within the 0.05% to 2% error range. The results of the other nine test candidate files have nearly 75% of their predictions within a 3% or less error while predicting RBS cost, and NED allows the user to make predictions of cost for all test cases within 7% of actual.

Simulation distinguishes between verification and validation—the former corresponds to debugging the model while the latter corresponds to assessing model correctness. A large-scale space-filling design such as the NOB acts a stress test on simulation models, often exposing software bugs and vulnerabilities. The NOB cannot establish validity, but the fact that NAVARM was able to successfully run all input configurations generated by the design lends credence to it as a well-verified model.

Another potential direction for future development is to pool all ten test cases to see whether a single comprehensive meta-model can be constructed. This would allow investigation of possible model commonalities across the scenarios.

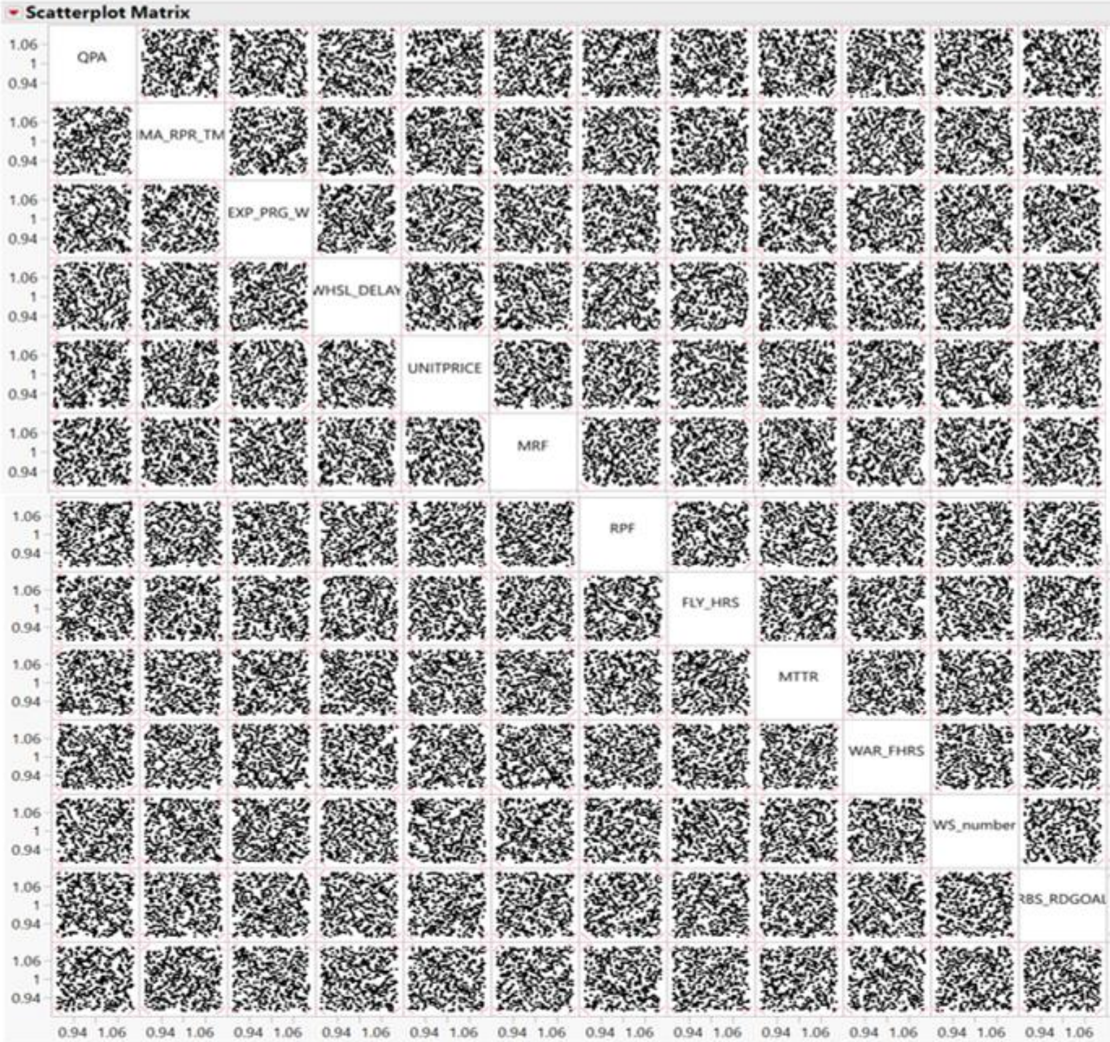
Lastly, a future study should consider different ranges of scaling than were used in the current work. This could change the sensitives of the response to the various factors as well as the degree of non-linearity or interaction effects.

APPENDIX A. 512 – POINT NOB DOE FACTOR CORRELATION AND SCATTERPLOT MATRIX

Correlations

	QPA	IMA_RPR_TM	EXP_PRG_W	WHSL_DELAY	UNITPRICE	MRF	RPF	FLY_HRS	MTTR	WAR_FHRS	WS_number	RBS_RDGOAL
QPA	1.0000	-0.0010	-0.0050	-0.0028	0.0095	-0.0077	0.0009	-0.0026	0.0080	-0.0006	-0.0002	0.0095
IMA_RPR_TM	-0.0010	1.0000	-0.0038	-0.0009	-0.0011	-0.0024	-0.0072	-0.0034	-0.0026	0.0016	-0.0048	-0.0052
EXP_PRG_W	-0.0050	-0.0038	1.0000	-0.0017	0.0035	0.0007	-0.0068	0.0047	-0.0016	-0.0081	0.0032	-0.0029
WHSL_DELAY	-0.0028	-0.0009	-0.0017	1.0000	-0.0025	-0.0032	0.0013	-0.0030	0.0015	0.0041	0.0038	-0.0002
UNITPRICE	0.0095	-0.0011	0.0035	-0.0025	1.0000	0.0069	-0.0058	-0.0082	0.0124	-0.0025	-0.0081	0.0027
MRF	-0.0077	-0.0024	0.0007	-0.0032	0.0069	1.0000	-0.0006	-0.0002	0.0012	0.0055	-0.0010	-0.0012
RPF	0.0009	-0.0072	-0.0068	0.0013	-0.0058	-0.0006	1.0000	0.0056	-0.0030	0.0000	-0.0000	0.0019
FLY_HRS	-0.0026	-0.0034	0.0047	-0.0030	-0.0082	-0.0002	0.0056	1.0000	-0.0001	0.0007	0.0009	-0.0006
MTTR	0.0080	-0.0026	-0.0016	0.0015	0.0124	0.0012	-0.0030	-0.0001	1.0000	-0.0019	0.0005	-0.0000
WAR_FHRS	-0.0006	0.0016	-0.0081	0.0041	-0.0025	0.0055	0.0000	0.0007	-0.0019	1.0000	0.0006	0.0019
WS_number	-0.0002	-0.0048	0.0032	0.0038	-0.0081	-0.0010	-0.0000	0.0009	0.0005	0.0006	1.0000	0.0004
RBS_RDGOAL	0.0095	-0.0052	-0.0029	-0.0002	0.0027	-0.0012	0.0019	-0.0006	-0.0000	0.0019	0.0004	1.0000
Demands	0.0014	0.0005	-0.0060	0.0047	0.0030	0.0025	0.0111	0.0115	0.0117	0.0101	0.0071	0.0039

Scatterplot Matrix



Note: Correlation and scatterplot matrix show that NOB DOE is space filling with no correlation. This makes for an excellent way to experiment with multiple factors covering their full spectrum.

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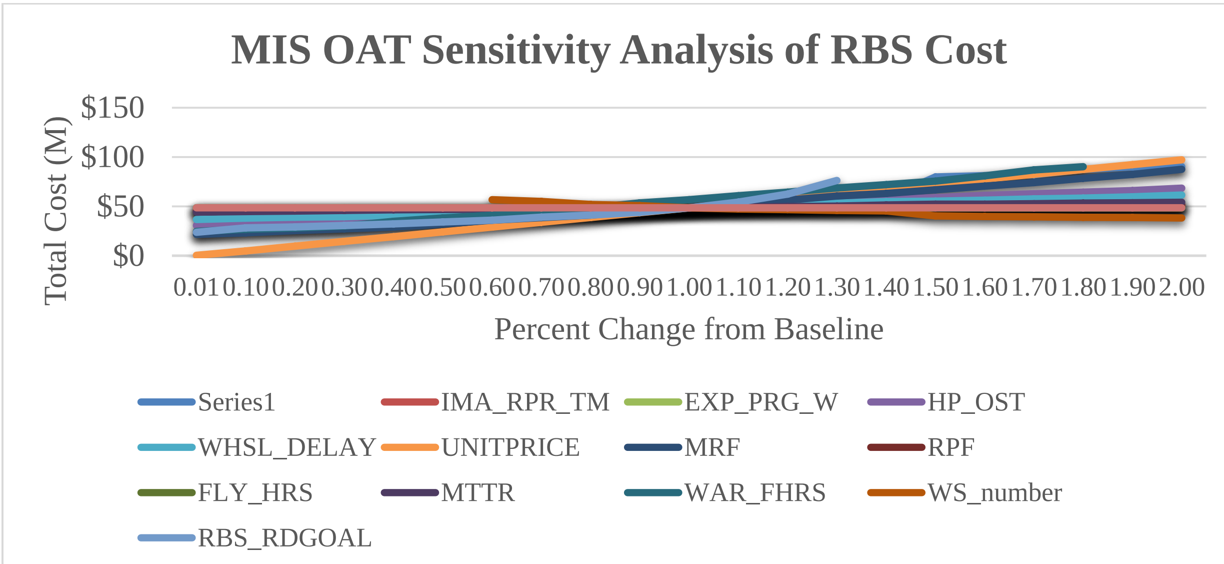
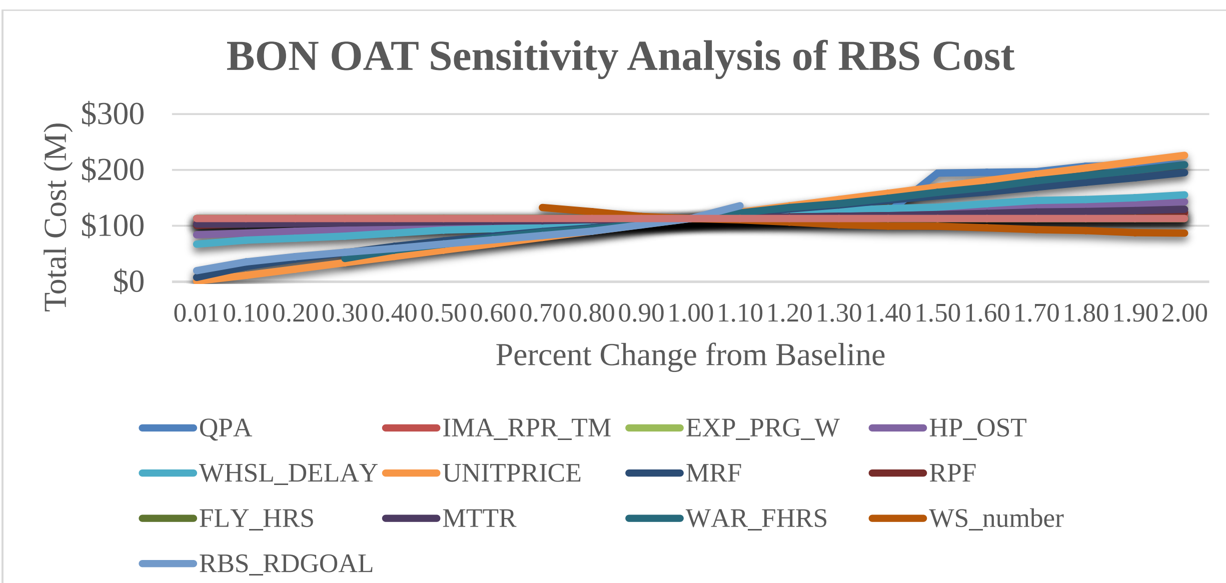
APPENDIX B. OAT SA GRAPHS OF MIS/BON/OCA/BAT

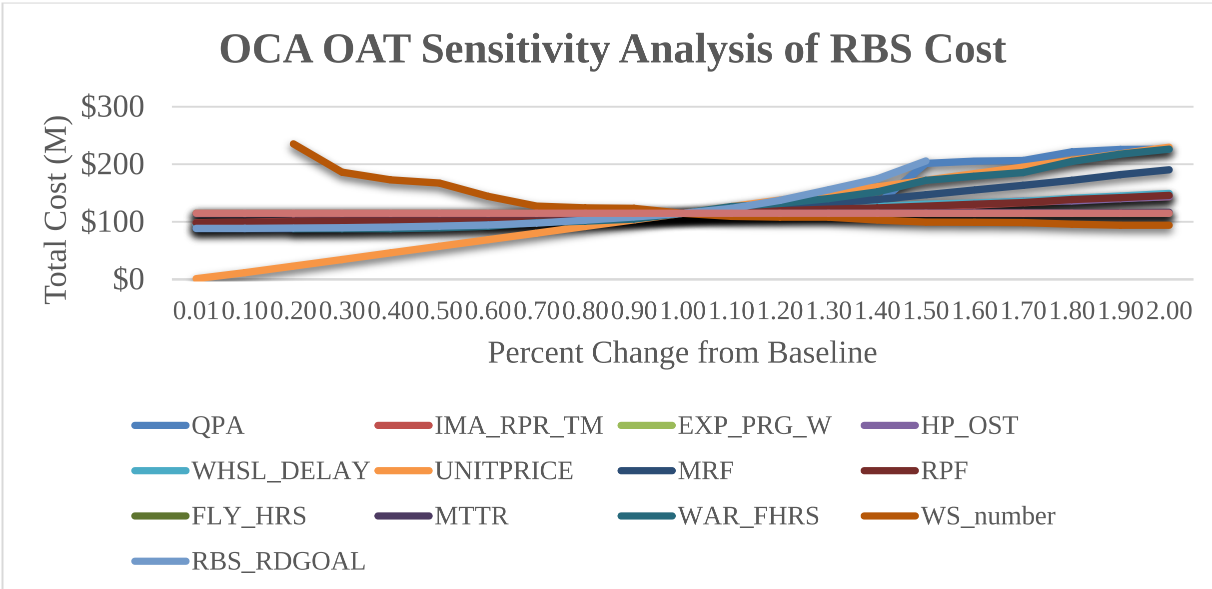
A. OAT DESIGN RESULTS FOR MIS



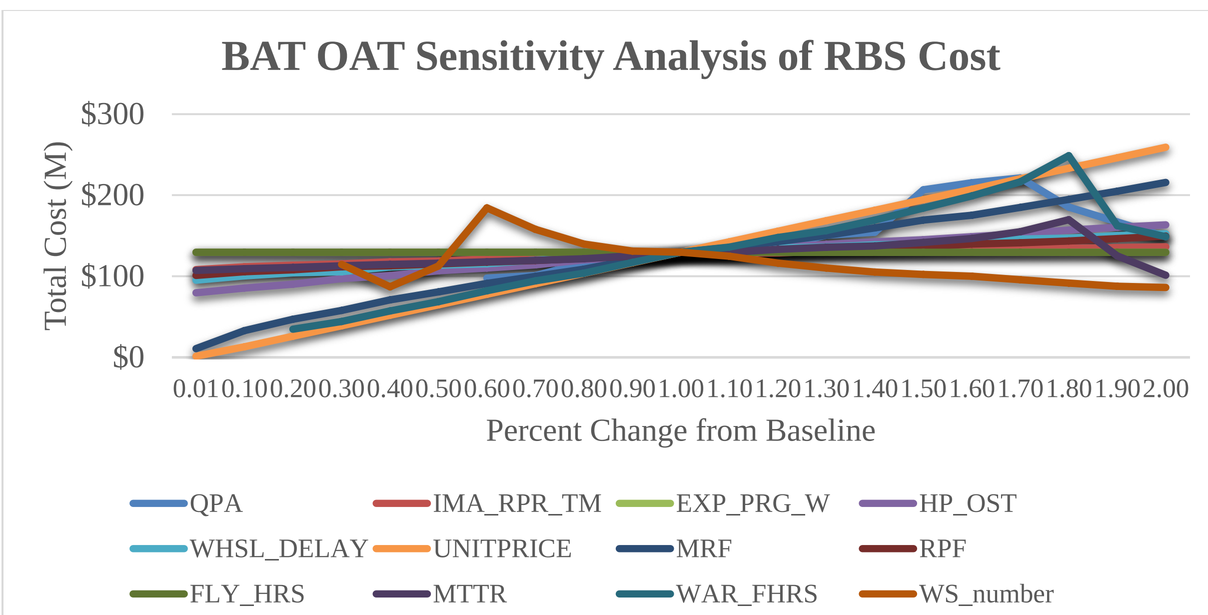
B. OAT DESIGN RESULTS FOR BON



C. OAT DESIGN RESULTS FOR OCA

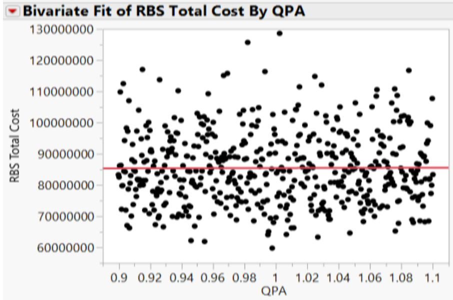


D. OAT DESIGN RESULTS FOR BAT



APPENDIX C. HST FACTOR BY OUTPUT SCATTER PLOTS

Bivariate Fit of RBS Total Cost By QPA



Linear Fit

Linear Fit

RBS Total Cost = 84464353 + 945605.98*QPA

Summary of Fit

RSquare	0.000023
RSquare Adj	-0.00194
Root Mean Square Error	11409161
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

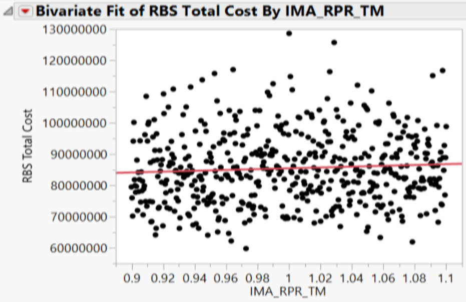
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.532e+12	1.532e+12	0.0118
Error	510	6.6386e+16	1.302e+14	Prob > F
C. Total	511	6.6388e+16		0.9137

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	84464353	8730914	9.67	<.0001*
QPA	945605.98	8716342	0.11	0.9137

a. QPA by RBS cost

Bivariate Fit of RBS Total Cost By IMA_RPR_TM



Linear Fit

Linear Fit

RBS Total Cost = 72189208 + 13220751*IMA_RPR_TM

Summary of Fit

RSquare	0.004511
RSquare Adj	0.002559
Root Mean Square Error	11383531
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

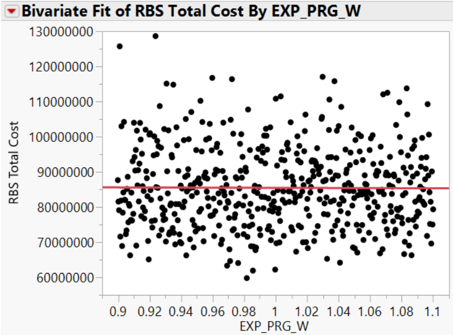
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.9947e+14	2.995e+14	2.3110
Error	510	6.6088e+16	1.296e+14	Prob > F
C. Total	511	6.6388e+16		0.1291

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	72189208	8711300	8.29	<.0001*
IMA_RPR_TM	13220751	8696761	1.52	0.1291

b. IMA_RPR_TM by RBS cost

Bivariate Fit of RBS Total Cost By EXP_PRG_W



Linear Fit

Linear Fit

RBS Total Cost = 86615193 - 1205234.8*EXP_PRG_W

Summary of Fit

RSquare	3.749e-5
RSquare Adj	-0.00192
Root Mean Square Error	11409079
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

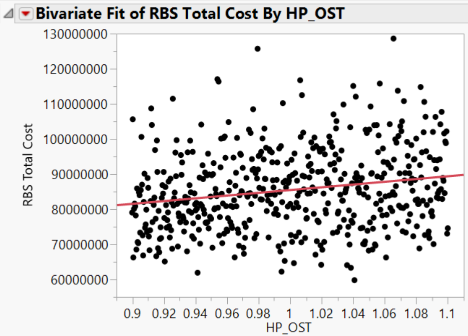
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.4888e+12	2.489e+12	0.0191
Error	510	6.6385e+16	1.302e+14	Prob > F
C. Total	511	6.6388e+16		0.8901

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	86615193	8730851	9.92	<.0001*
EXP_PRG_W	-1205235	8716279	-0.14	0.8901

a. EXP_PRG_W by RBS cost

Bivariate Fit of RBS Total Cost By HP_OST



Linear Fit

Linear Fit

RBS Total Cost = 46075191 + 39334767*HP_OST

Summary of Fit

RSquare	0.03993
RSquare Adj	0.038048
Root Mean Square Error	11179183
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

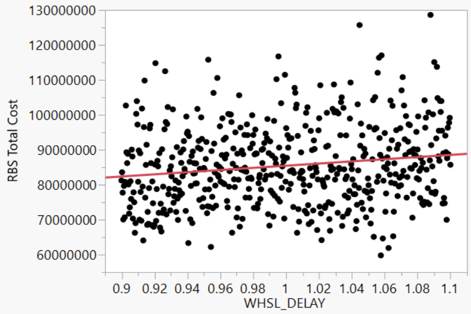
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.6509e+15	2.651e+15	21.2115
Error	510	6.3737e+16	1.25e+14	Prob > F
C. Total	511	6.6388e+16		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	46075191	8554922	5.39	<.0001*
HP_OST	39334767	8540644	4.61	<.0001*

b. HP_OST by RBS cost

Bivariate Fit of RBS Total Cost By WHSL_DELAY



Linear Fit

Linear Fit

RBS Total Cost = 54539840 + 30870119*WHSL_DELAY

Summary of Fit

RSquare	0.024594
RSquare Adj	0.022681
Root Mean Square Error	11268120
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

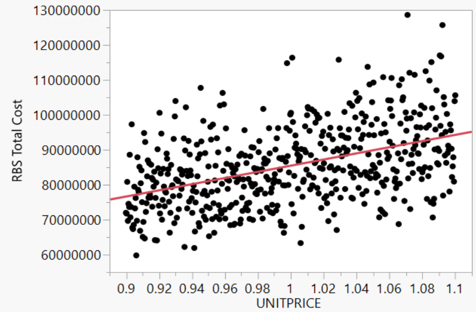
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.6327e+15	1.633e+15	12.8592
Error	510	6.4755e+16	1.27e+14	Prob > F
C. Total	511	6.6388e+16		0.0004*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	54539840	8622981	6.32	<.0001*
WHSL_DELAY	30870119	8608590	3.59	0.0004*

a. WHSL_DELAY by RBS cost

Bivariate Fit of RBS Total Cost By UNITPRICE



Linear Fit

Linear Fit

RBS Total Cost = -2788655 + 88198614*UNITPRICE

Summary of Fit

RSquare	0.200759
RSquare Adj	0.199192
Root Mean Square Error	10199940
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

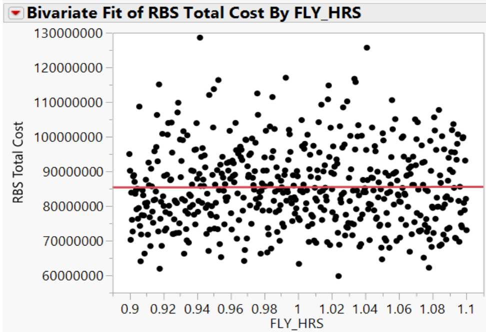
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.3328e+16	1.333e+16	128.1053
Error	510	5.306e+16	1.04e+14	Prob > F
C. Total	511	6.6388e+16		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2788655	7805552	-0.36	0.7210
UNITPRICE	88198614	7792525	11.32	<.0001*

b. UNITPRICE by RBS cost

Bivariate Fit of RBS Total Cost By FLY_HRS



Linear Fit

Linear Fit

RBS Total Cost = 84538438 + 871521.16*FLY_HRS

Summary of Fit

RSquare	1.96e-5
RSquare Adj	-0.00194
Root Mean Square Error	11409181
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

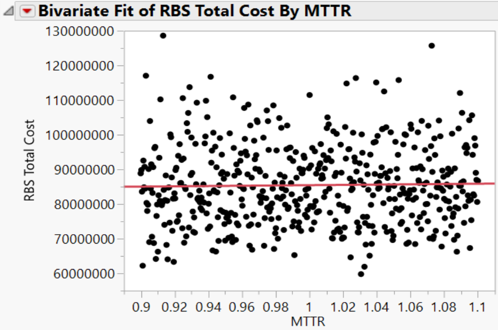
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.3014e+12	1.301e+12	0.0100
Error	510	6.6386e+16	1.302e+14	Prob > F
C. Total	511	6.6388e+16		0.9204

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	84538438	8730929	9.68	<.0001*
FLY_HRS	871521.16	8716357	0.10	0.9204

a. FLY_HRS by RBS cost

Bivariate Fit of RBS Total Cost By MTTR



Linear Fit

Linear Fit

RBS Total Cost = 81288448 + 4121511.2*MTTR

Summary of Fit

RSquare	0.000438
RSquare Adj	-0.00152
Root Mean Square Error	11406792
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

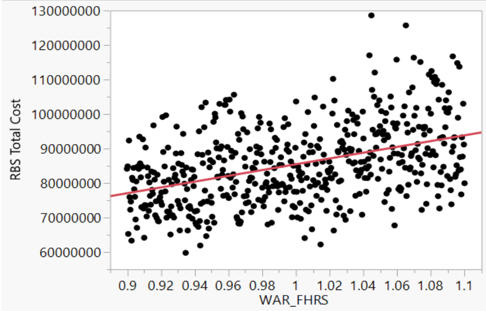
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.9104e+13	2.91e+13	0.2237
Error	510	6.6359e+16	1.301e+14	Prob > F
C. Total	511	6.6388e+16		0.6365

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	81288448	8729101	9.31	<.0001*
MTTR	4121511.2	8714532	0.47	0.6365

b. MTTR by RBS cost

Bivariate Fit of RBS Total Cost By WAR_FHRS



Linear Fit

Linear Fit

RBS Total Cost = 1431195.7 + 83978763*WAR_FHRS

Summary of Fit

RSquare	0.182008
RSquare Adj	0.180404
Root Mean Square Error	10318897
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

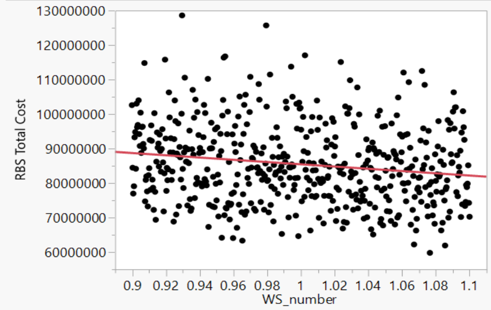
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.2083e+16	1.208e+16	113.4779
Error	510	5.4305e+16	1.065e+14	Prob > F
C. Total	511	6.6388e+16		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	1431195.7	7896584	0.18	0.8562
WAR_FHRS	83978763	7883405	10.65	<.0001*

a. WAR_FHRS by RBS cost

Bivariate Fit of RBS Total Cost By WS_number



Linear Fit

Linear Fit

RBS Total Cost = 118030164 - 32620205*WS_number

Summary of Fit

RSquare	0.027462
RSquare Adj	0.025555
Root Mean Square Error	11251544
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

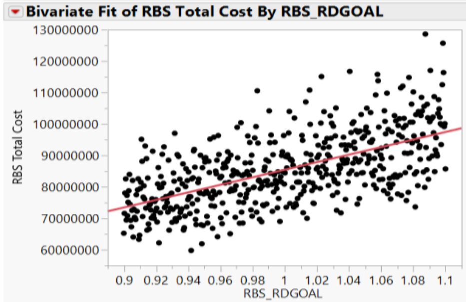
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1.8231e+15	1.823e+15	14.4008
Error	510	6.4565e+16	1.266e+14	Prob > F
C. Total	511	6.6388e+16		0.0002*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	118030164	8610297	13.71	<.0001*
WS_number	-32620205	8595926	-3.79	0.0002*

b. WS_number by RBS cost

Bivariate Fit of RBS Total Cost By RBS_RDGOAL



Linear Fit

Linear Fit

RBS Total Cost = -34589187 + 119999145*RBS_RDGOAL

Summary of Fit

RSquare	0.371627
RSquare Adj	0.370395
Root Mean Square Error	9044143
Mean of Response	85409959
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.4671e+16	2.467e+16	301.6202
Error	510	4.1716e+16	8.18e+13	Prob > F
C. Total	511	6.6388e+16		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-34589187	6921072	-5.00	<.0001*
RBS_RDGOAL	119999145	6909521	17.37	<.0001*

a. RBS_RDGOAL by RBS cost

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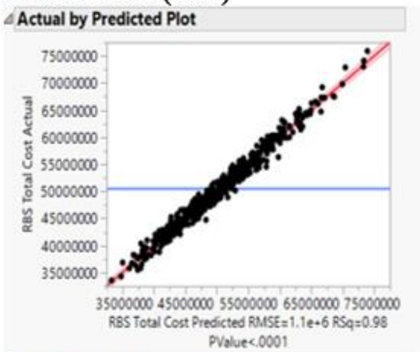
APPENDIX D. TEST CANDIDATE FILE META-MODELS

A. LEM RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



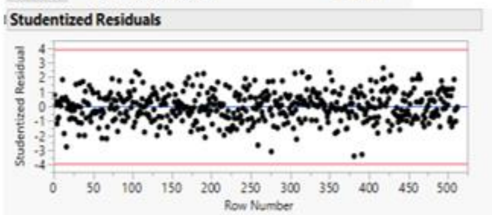
Summary of Fit

RSquare	0.977973
RSquare Adj	0.976887
Root Mean Square Error	1092954
Mean of Response	50590103
Observations (or Sum Wgts)	512

Analysis of Variance

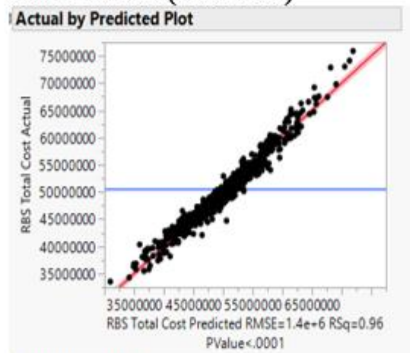
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	24	2.5828e+16	1.076e+15	900.9058
Error	487	5.8174e+14	1.195e+12	Prob > F
C. Total	511	2.641e+16		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



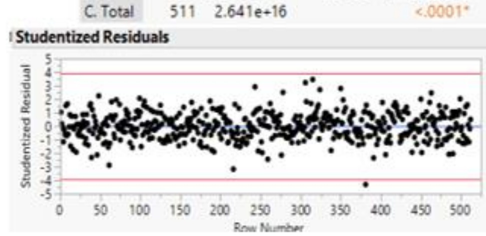
Summary of Fit

RSquare	0.962884
RSquare Adj	0.962294
Root Mean Square Error	1395977
Mean of Response	50590103
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	2.543e+16	3.179e+15	1631.153
Error	503	9.8022e+14	1.949e+12	Prob > F
C. Total	511	2.641e+16		<.0001*

Studentized Residuals

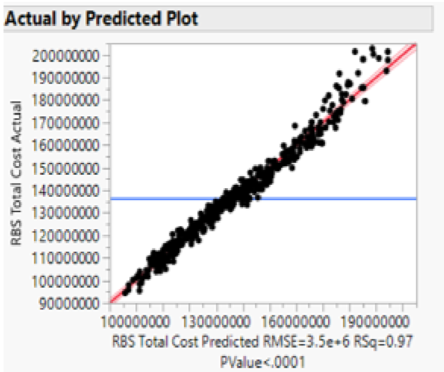


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	68797509	844261.5	81.49	<.0001*
WAR_FHRS	54440687	841658.5	64.68	<.0001*
UNITPRICE	52732352	842053.3	62.62	<.0001*
RPF	33416111	844843.1	39.55	<.0001*
IMA_RPR_TM	32034809	844078.9	37.95	<.0001*
MRF	30964751	853496	36.28	<.0001*
HP_OST	22481000	843743.8	26.64	<.0001*
WS_number	-20775080	842854.1	-24.65	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	105971238	14737414	7.19	<.0001*
(MRF-1)*(WAR_FHRS-1)	88555450	14919574	5.94	<.0001*
(IMA_RPR_TM-1)*(RBS_RDGOAL-1)	-84570655	15230518	-5.55	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	73821204	15004922	4.92	<.0001*
WHSL_DELAY	3904844.7	845597.5	4.62	<.0001*
(WS_number-1)*(RBS_RDGOAL-1)	-66857656	15071608	-4.44	<.0001*
(UNITPRICE-1)*(WAR_FHRS-1)	64875172	14838464	4.37	<.0001*
(RPF-1)*(RBS_RDGOAL-1)	-63506187	14531401	-4.37	<.0001*
(HP_OST-1)*(WAR_FHRS-1)	59250914	14573069	4.07	<.0001*
(IMA_RPR_TM-1)*(WAR_FHRS-1)	54861415	14519532	3.78	0.0002*
(RPF-1)*(WAR_FHRS-1)	52426474	14624794	3.58	0.0004*
(WAR_FHRS-1)*(WAR_FHRS-1)	55921933	16365083	3.42	0.0007*
(WS_number-1)*(WS_number-1)	52635435	16450553	3.20	0.0015*
QPA	2419198.7	855699.4	2.83	0.0049*
(WHSL_DELAY-1)*(WAR_FHRS-1)	37981119	14948886	2.54	0.0114*
(IMA_RPR_TM-1)*(UNITPRICE-1)	36870307	14763032	2.50	0.0128*

B. BAT RBS REGRESSION ANALYSIS

Meta-model (Full)

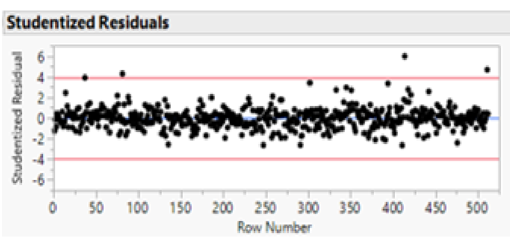


Summary of Fit

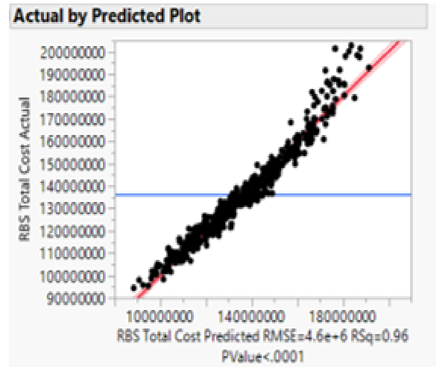
RSquare	0.974835
RSquare Adj	0.973864
Root Mean Square Error	3463740
Mean of Response	1.364e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	19	2.2866e+17	1.203e+16	1003.123
Error	492	5.9028e+15	1.2e+13	Prob > F
C. Total	511	2.3457e+17		<.0001*



Meta-model (Reduced)

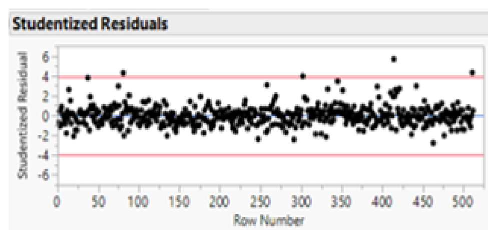


Summary of Fit

RSquare	0.955537
RSquare Adj	0.95474
Root Mean Square Error	4558055
Mean of Response	1.364e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	2.2414e+17	2.49e+16	1198.708
Error	502	1.0429e+16	2.078e+13	Prob > F
C. Total	511	2.3457e+17		<.0001*

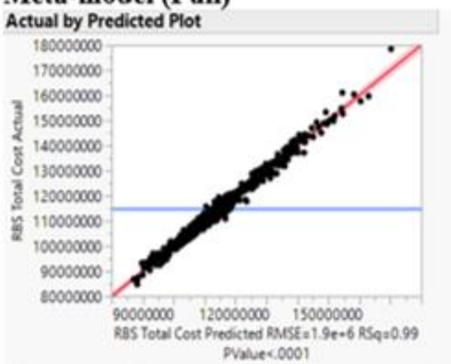


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	310720952	2811367	110.52	<.0001*
UNITPRICE	140665919	2668381	52.72	<.0001*
WAR_FHRS	123193421	2663120	46.26	<.0001*
MRF	90252594	2681321	33.66	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	1.2155e+9	55192319	22.02	<.0001*
HP_OST	48339132	2672114	18.09	<.0001*
WS_number	-43400469	2650703	-16.37	<.0001*
MTTR	30782530	2653275	11.60	<.0001*
RPF	27208421	2673996	10.18	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	470050531	49476341	9.50	<.0001*
(WS_number-1)*(RBS_RDGOAL-1)	-4.096e+8	49306218	-8.31	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	326736877	49240576	6.64	<.0001*
QPA	17615793	2681224	6.57	<.0001*
WHSL_DELAY	16649618	2678523	6.22	<.0001*
MA_RPR_TM	14955030	2659271	5.62	<.0001*
(MTTR-1)*(RBS_RDGOAL-1)	248014445	48310176	5.13	<.0001*
(RPF-1)*(RBS_RDGOAL-1)	184413138	48769292	3.78	0.0002*
(MRF-1)*(RBS_RDGOAL-1)	158158248	48949744	3.23	0.0013*
(WHSL_DELAY-1)*(RBS_RDGOAL-1)	-1.28e+8	49368257	-2.59	0.0098*

C. BON RBS REGRESSION ANALYSIS

Meta-model (Full)

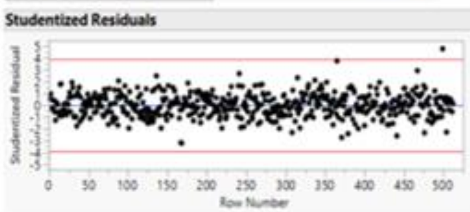


Summary of Fit

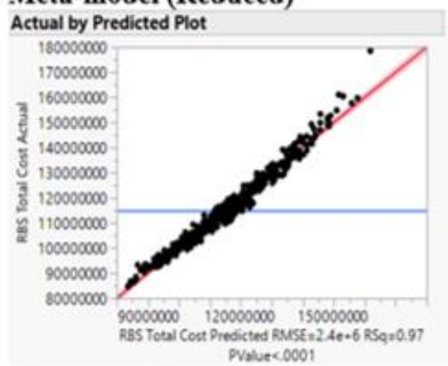
RSquare	0.985272
RSquare Adj	0.984514
Root Mean Square Error	1850437
Mean of Response	1.149e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	25	1.1132e+17	4.453e+15	1300.468
Error	486	1.6641e+15	3.424e+12	Prob > F
C. Total	511	1.1299e+17		<.0001*



Meta-model (Reduced)

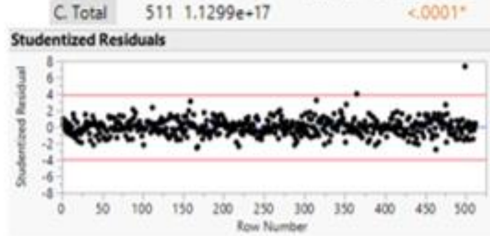


Summary of Fit

RSquare	0.973713
RSquare Adj	0.973242
Root Mean Square Error	2432405
Mean of Response	1.149e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	1.1002e+17	1.222e+16	2066.090
Error	502	2.9701e+15	5.917e+12	Prob > F
C. Total	511	1.1299e+17		<.0001*



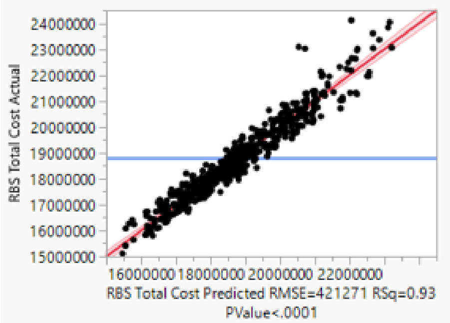
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	169839809	1441351	117.83	<.0001*
UNITPRICE	117624790	1440302	81.67	<.0001*
WAR_FHRS	93872658	1441042	65.14	<.0001*
MRF	81205221	1449723	56.01	<.0001*
WHSL_DELAY	39310111	1441156	27.28	<.0001*
HP_OST	32393628	1444781	22.42	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	493419063	27952392	17.65	<.0001*
MTTR	13949550	1446657	9.64	<.0001*
WS_number	-13548607	1435902	-9.44	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	216585022	25484978	8.50	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	199234228	24854576	8.02	<.0001*
RPF	11167076	1440441	7.75	<.0001*
(MRF-1)*(RBS_RDGOAL-1)	173209950	24805399	6.98	<.0001*
IMA_RPR_TM	6677511.9	1438073	4.64	<.0001*
(RPF-1)*(RBS_RDGOAL-1)	97053740	24688345	3.93	<.0001*
(UNITPRICE-1)*(WAR_FHRS-1)	91067892	25238910	3.61	0.0003*
(FLY_HRS-1)*(RBS_RDGOAL-1)	86260504	25183781	3.43	0.0007*
(MTTR-1)*(WS_number-1)	-83891714	25803560	-3.25	0.0012*
(WS_number-1)*(RBS_RDGOAL-1)	-82139889	25629024	-3.20	0.0014*
(MRF-1)*(WAR_FHRS-1)	71881707	25625028	2.81	0.0052*
(WHSL_DELAY-1)*(WAR_FHRS-1)	70163878	25421387	2.76	0.0060*
(RBS_RDGOAL-1)*(Demands-1)	68685372	24939533	2.75	0.0061*
(UNITPRICE-1)*(MRF-1)	69375945	25343096	2.74	0.0064*
FLY_HRS	-4104943	1430103	-0.29	0.7742

D. NOR RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



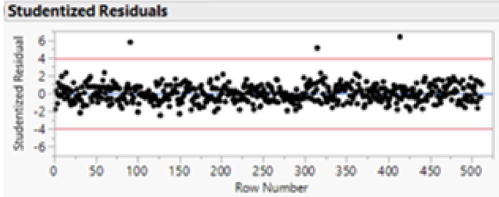
Summary of Fit

RSquare	0.932814
RSquare Adj	0.931336
Root Mean Square Error	421271.1
Mean of Response	18805769
Observations (or Sum Wgts)	512

Analysis of Variance

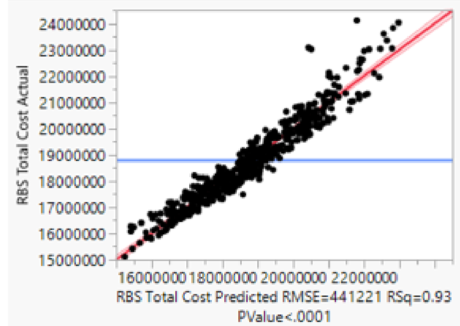
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	11	1.232e+15	1.12e+14	631.0923
Error	500	8.8735e+13	1.775e+11	Prob > F
C. Total	511	1.3207e+15		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



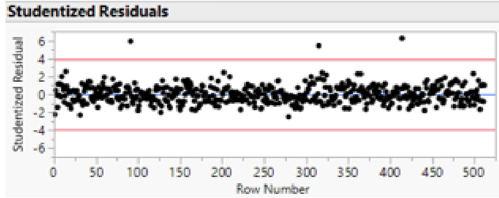
Summary of Fit

RSquare	0.925416
RSquare Adj	0.924679
Root Mean Square Error	441220.6
Mean of Response	18805769
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	1.2222e+15	2.444e+14	1255.652
Error	506	9.8506e+13	1.947e+11	Prob > F
C. Total	511	1.3207e+15		<.0001*

Studentized Residuals



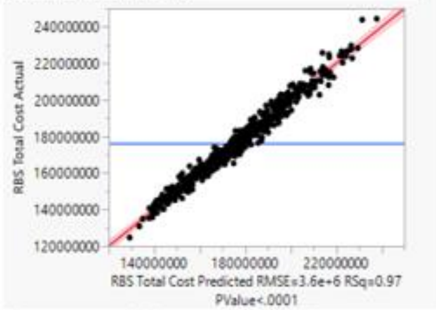
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
UNITPRICE	19010967	323898.4	58.69	<.0001*
RBS_RDGOAL	10548531	323658.2	32.59	<.0001*
WAR_FHRS	9661943.6	325112.7	29.72	<.0001*
MRF	8398381.3	322666.4	26.03	<.0001*
HP_OST	7619183.5	324705.8	23.46	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	23926122	6300987	3.80	0.0002*
QPA	1126548.5	322900.1	3.49	0.0005*
(MRF-1)*(RBS_RDGOAL-1)	17900854	5569015	3.21	0.0014*
(HP_OST-1)*(MRF-1)	17216689	5613170	3.07	0.0023*
(UNITPRICE-1)*(WAR_FHRS-1)	16143148	5684816	2.84	0.0047*
(HP_OST-1)*(UNITPRICE-1)	14377211	5618919	2.56	0.0108*

E. MAL RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



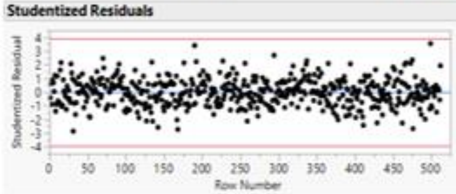
Summary of Fit

RSquare	0.971066
RSquare Adj	0.969515
Root Mean Square Error	3628082
Mean of Response	1.763e+8
Observations (or Sum Wgts)	512

Analysis of Variance

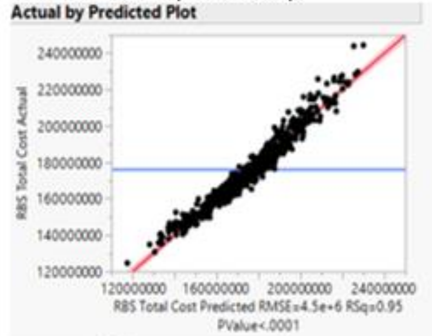
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	26	2.1426e+17	8.241e+15	626.0473
Error	485	6.384e+15	1.316e+13	Prob > F
C. Total	511	2.2064e+17		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



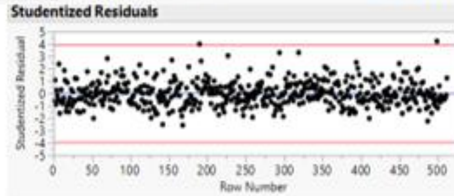
Summary of Fit

RSquare	0.954071
RSquare Adj	0.953248
Root Mean Square Error	4492968
Mean of Response	1.763e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	2.1051e+17	2.339e+16	1158.665
Error	502	1.0134e+16	2.019e+13	Prob > F
C. Total	511	2.2064e+17		<.0001*

Studentized Residuals

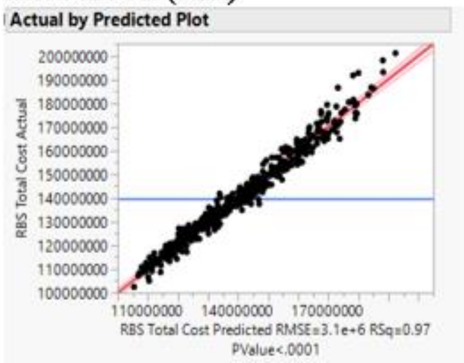


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
WAR_FHRS	207700717	2841509	73.10	<.0001*
UNITPRICE	179824747	2804042	64.13	<.0001*
RBS_RDGOAL	330938278	6392589	51.77	<.0001*
MRF	104383939	2851774	36.60	<.0001*
RPF	96966322	2807685	34.54	<.0001*
IMA_RPR_TM	85044390	2831884	30.03	<.0001*
WS_number	-75655175	2803672	-26.98	<.0001*
WHSL_DELAY	48612758	2823398	17.22	<.0001*
HP_OST	41950080	2824989	14.85	<.0001*
MTTR	22203486	2812992	7.89	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-0.95)	876318702	1.16e+8	7.55	<.0001*
(RPF-1)*(RBS_RDGOAL-0.95)	715476780	1.114e+8	6.42	<.0001*
(IMA_RPR_TM-1)*(RBS_RDGOAL-0.95)	591832500	1.117e+8	5.30	<.0001*
(IMA_RPR_TM-1)*(WAR_FHRS-1)	242351787	48729206	4.97	<.0001*
(RBS_RDGOAL-0.95)*(RBS_RDGOAL-0.95)	1.1472e+9	2.366e+8	4.85	<.0001*
(UNITPRICE-1)*(MRF-1)	230734269	49572153	4.65	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-0.95)	478512803	1.112e+8	4.30	<.0001*
(WS_number-1)*(RBS_RDGOAL-0.95)	-4.493e+8	1.118e+8	-4.02	<.0001*
(UNITPRICE-1)*(WAR_FHRS-1)	190320656	49090583	3.88	0.0001*
(QPA-1)*(WHSL_DELAY-1)	-1.762e+8	49597450	-3.55	0.0004*
(WAR_FHRS-1)*(WAR_FHRS-1)	161933691	55121412	2.94	0.0035*
(RPF-1)*(WAR_FHRS-1)	144415578	49594593	2.91	0.0038*
(WAR_FHRS-1)*(WS_number-1)	-1.363e+8	49504668	-2.75	0.0061*
(IMA_RPR_TM-1)*(UNITPRICE-1)	123707102	49128817	2.52	0.0121*
(IMA_RPR_TM-1)*(RPF-1)	124494452	49689705	2.51	0.0126*
QPA	70003756	2834653	0.25	0.8050

F. IWO RBS REGRESSION ANALYSIS

Meta-model (Full)

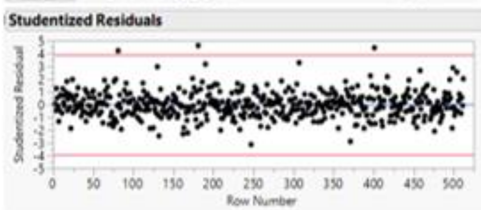


Summary of Fit

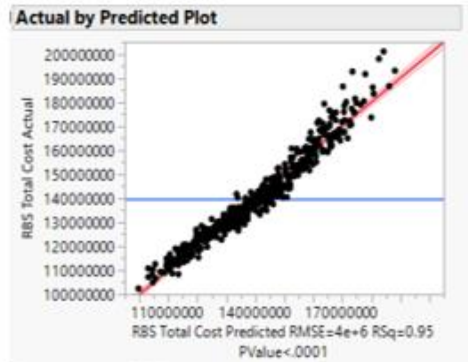
RSquare	0.972151
RSquare Adj	0.970718
Root Mean Square Error	3130217
Mean of Response	1.398e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	25	1.6623e+17	6.649e+15	678.5996
Error	486	4.762e+15	9.798e+12	Prob > F
C. Total	511	1.7099e+17		<.0001*



Meta-model (Reduced)

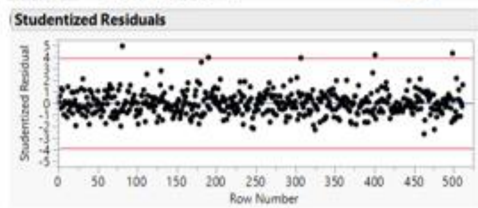


Summary of Fit

RSquare	0.95365
RSquare Adj	0.952725
Root Mean Square Error	3977324
Mean of Response	1.398e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	1.6306e+17	1.631e+16	1030.804
Error	501	7.9254e+15	1.582e+13	Prob > F
C. Total	511	1.7099e+17		<.0001*



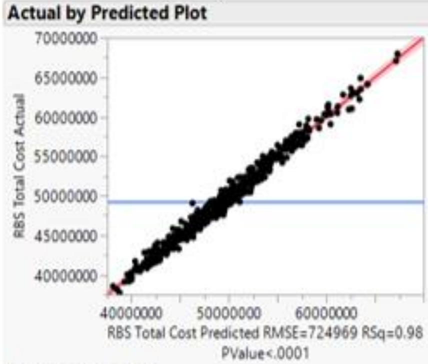
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	273000570	2923659	93.38	<.0001*
UNITPRICE	145570512	2413765	60.31	<.0001*
WAR_FHRS	121961800	2435287	50.08	<.0001*
MRF	97693809	2450502	39.87	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	1.3662e+9	62472485	21.87	<.0001*
WS_number	-48728083	2412727	-20.20	<.0001*
HP_OST	42505009	2440031	17.42	<.0001*
WHSL_DELAY	34019642	2440661	13.94	<.0001*
MTTR	34096827	2448595	13.93	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	518012238	51072637	10.14	<.0001*
WS_number-1)*(RBS_RDGOAL-1)	-4.507e+8	51645351	-8.73	<.0001*
PF	17295662	2447294	7.07	<.0001*
MTTR-1)*(RBS_RDGOAL-1)	326598949	48925069	6.68	<.0001*
UNITPRICE-1)*(RBS_RDGOAL-1)	313675670	51413030	6.10	<.0001*
MRF-1)*(RBS_RDGOAL-1)	262497800	50704373	5.18	<.0001*
QPA	11253855	2442245	4.61	<.0001*
MRF-1)*(WS_number-1)	-1.802e+8	42850234	-4.21	<.0001*
UNITPRICE-1)*(WAR_FHRS-1)	154809956	42553062	3.64	0.0003*
UNITPRICE-1)*(MTTR-1)	150953856	41666713	3.62	0.0003*
WAR_FHRS-1)*(WS_number-1)	-1.519e+8	43016669	-3.53	0.0005*
QPA-1)*(MTTR-1)	133122755	42344163	3.14	0.0018*
MRF-1)*(WAR_FHRS-1)	126682688	42613742	2.97	0.0031*
MA_RPR_TM	69735242	2406572	2.90	0.0039*
MRF-1)*(MTTR-1)	117499298	40923754	2.87	0.0043*
RPF-1)*(RBS_RDGOAL-1)	140878184	50401614	2.80	0.0054*

G. MIS RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



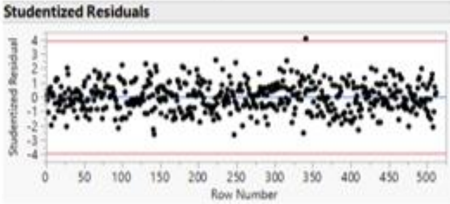
Summary of Fit

RSquare	0.983102
RSquare Adj	0.982269
Root Mean Square Error	724968.5
Mean of Response	49240315
Observations (or Sum Wgts)	512

Analysis of Variance

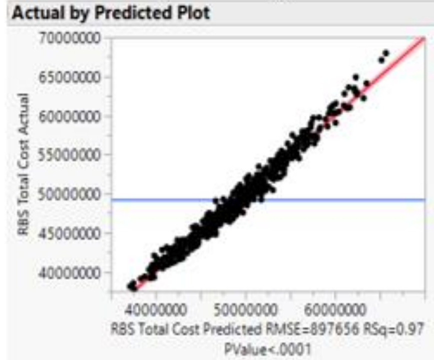
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	24	1.4891e+16	6.205e+14	1180.538
Error	487	2.5596e+14	5.256e+11	Prob > F
C. Total	511	1.5147e+16		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



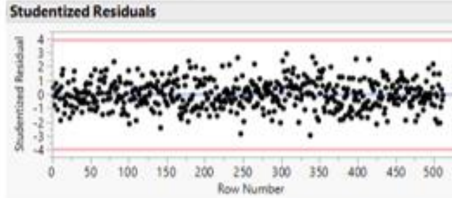
Summary of Fit

RSquare	0.973242
RSquare Adj	0.972816
Root Mean Square Error	897655.9
Mean of Response	49240315
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	1.4742e+16	1.843e+15	2286.872
Error	503	4.0531e+14	8.058e+11	Prob > F
C. Total	511	1.5147e+16		<.0001*

Studentized Residuals



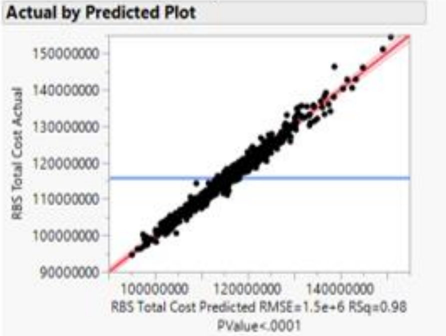
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	51606742	561306.7	91.94	<.0001*
UNITPRICE	49694952	559692.3	88.79	<.0001*
MRF	36044619	565483.5	63.74	<.0001*
WAR_FHRS	33572104	558952.8	60.06	<.0001*
HP_OST	22781453	562166.2	40.52	<.0001*
WS_number	-12164783	556014.2	-21.88	<.0001*
WHSL_DELAY	8747908.2	562636.8	15.55	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	95885801	9870111	9.71	<.0001*
MTTR	4129004.8	561997.9	7.35	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	69325140	10012185	6.92	<.0001*
RPF	3014496.1	566552.5	5.32	<.0001*
IMA_RPR_TM	2656178.1	558664.2	4.75	<.0001*
QPA	2328510.7	569544.2	4.09	<.0001*
(WS_number-1)*(RBS_RDGOAL-1)	-39867773	10026002	-3.98	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	41908539	10880402	3.85	0.0001*
(MRF-1)*(WS_number-1)	-37869973	9964089	-3.80	0.0002*
(WAR_FHRS-1)*(WS_number-1)	-36993153	9885263	-3.74	0.0002*
(MRF-1)*(WAR_FHRS-1)	36165387	9943034	3.64	0.0003*
(QPA-1)*(MTTR-1)	33621269	9846426	3.41	0.0007*
(UNITPRICE-1)*(MRF-1)	33456922	9909821	3.38	0.0008*
(UNITPRICE-1)*(WAR_FHRS-1)	32637117	9832229	3.32	0.0010*
(WHSL_DELAY-1)*(WS_number-1)	-32184120	9866793	-3.26	0.0012*
(QPA-1)*(WHSL_DELAY-1)	-32178961	9958210	-3.23	0.0013*
(HP_OST-1)*(WAR_FHRS-1)	26508347	9671862	2.74	0.0064*

H. OCA RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



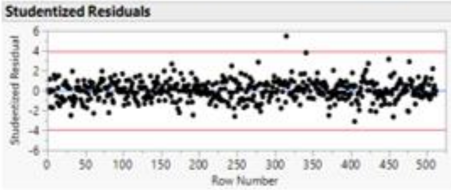
Summary of Fit

RSquare	0.977588
RSquare Adj	0.976239
Root Mean Square Error	1532184
Mean of Response	1.159e+8
Observations (or Sum Wgts)	512

Analysis of Variance

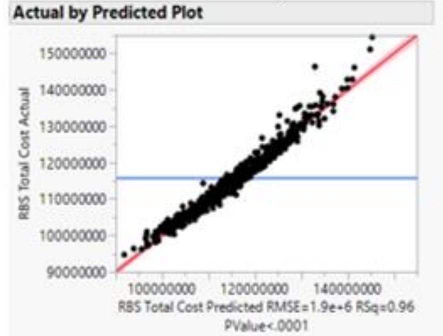
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	29	4.9356e+16	1.702e+15	724.9679
Error	482	1.1315e+15	2.348e+12	Prob > F
C. Total	511	5.0487e+16		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



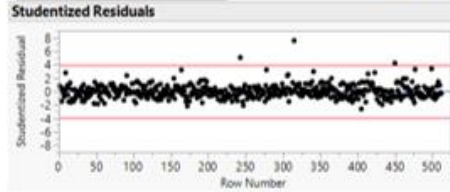
Summary of Fit

RSquare	0.964258
RSquare Adj	0.963617
Root Mean Square Error	1895954
Mean of Response	1.159e+8
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	4.8683e+16	5.409e+15	1504.799
Error	502	1.8045e+15	3.595e+12	Prob > F
C. Total	511	5.0487e+16		<.0001*

Studentized Residuals



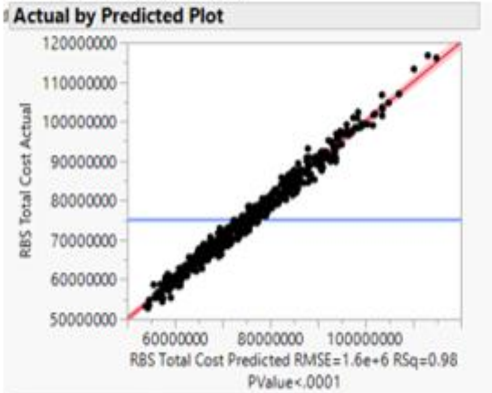
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
UNITPRICE	118991962	1192590	99.78	<.0001*
RBS_RDGOAL	74775187	1196701	62.48	<.0001*
WAR_FHRS	49471032	1186757	41.69	<.0001*
MRF	49858738	1202449	41.46	<.0001*
HP_OST	27863390	1193234	23.35	<.0001*
IMA_RPR_TM	23026387	1190749	19.34	<.0001*
WHSL_DELAY	22749541	1193701	19.06	<.0001*
RPF	21332433	1194134	17.86	<.0001*
WS_number	-16302830	1185907	-13.75	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	127180350	23177034	5.49	<.0001*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	112628759	20742023	5.43	<.0001*
(WAR_FHRS-1)*(WAR_FHRS-1)	113200793	23043205	4.91	<.0001*
(MRF-1)*(RBS_RDGOAL-1)	99081343	20792897	4.77	<.0001*
(HP_OST-1)*(RBS_RDGOAL-1)	95797312	20690525	4.63	<.0001*
(WAR_FHRS-1)*(WS_number-1)	-97261768	21066789	-4.62	<.0001*
(HP_OST-1)*(WAR_FHRS-1)	79306618	20473788	3.87	0.0001*
(MRF-1)*(WAR_FHRS-1)	78641461	20926617	3.76	0.0002*
(RPF-1)*(RBS_RDGOAL-1)	76584507	20399516	3.75	0.0002*
(WHSL_DELAY-1)*(WAR_FHRS-1)	77049150	21031633	3.66	0.0003*
(WS_number-1)*(WS_number-1)	82814809	22942240	3.61	0.0003*
(HP_OST-1)*(MRF-1)	73414366	20538991	3.57	0.0004*
(UNITPRICE-1)*(RBS_RDGOAL-1)	69956565	21124814	3.31	0.0010*
(IMA_RPR_TM-1)*(RPF-1)	67498444	20936592	3.22	0.0014*
(WHSL_DELAY-1)*(UNITPRICE-1)	64286993	20556826	3.13	0.0019*
(WS_number-1)*(RBS_RDGOAL-1)	-61843536	21234303	-2.91	0.0038*
(IMA_RPR_TM-1)*(WAR_FHRS-1)	57826899	20419922	2.83	0.0048*
(UNITPRICE-1)*(MRF-1)	58134011	21012633	2.77	0.0059*
(IMA_RPR_TM-1)*(RBS_RDGOAL-1)	58948326	21331321	2.76	0.0059*
(MRF-1)*(WS_number-1)	-52370732	20951662	-2.50	0.0128*

I. DEN RBS REGRESSION ANALYSIS

Meta-model (Full)

Actual by Predicted Plot



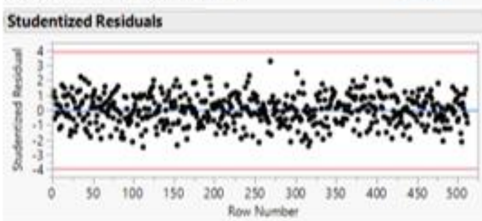
Summary of Fit

RSquare	0.980518
RSquare Adj	0.979807
Root Mean Square Error	1638973
Mean of Response	75216261
Observations (or Sum Wgts)	512

Analysis of Variance

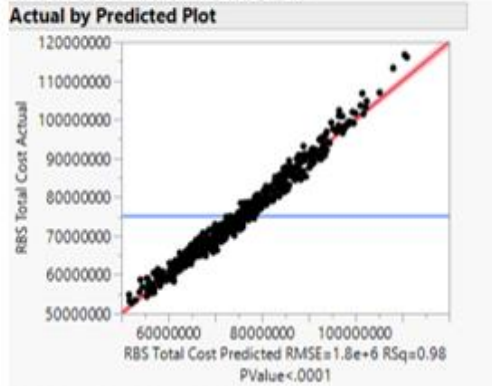
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	18	6.6654e+16	3.703e+15	1378.502
Error	493	1.3243e+15	2.686e+12	Prob > F
C. Total	511	6.7978e+16		<.0001*

Studentized Residuals



Meta-model (Reduced)

Actual by Predicted Plot



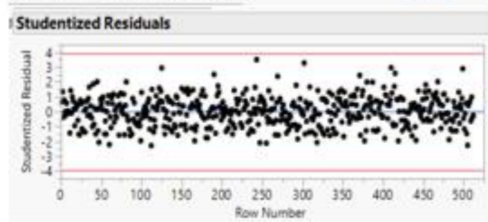
Summary of Fit

RSquare	0.975448
RSquare Adj	0.975058
Root Mean Square Error	1821543
Mean of Response	75216261
Observations (or Sum Wgts)	512

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	6.6309e+16	8.289e+15	2498.064
Error	503	1.669e+15	3.318e+12	Prob > F
C. Total	511	6.7978e+16		<.0001*

Studentized Residuals



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
RBS_RDGOAL	140779143	1268823	110.95	<.0001*
UNITPRICE	78005821	1265679	61.63	<.0001*
WAR_FHRS	65918743	1275799	51.67	<.0001*
MRF	64289693	1269165	50.66	<.0001*
WHSL_DELAY	39170067	1260933	31.06	<.0001*
HP_OST	23174409	1267074	18.29	<.0001*
(RBS_RDGOAL-1)*(RBS_RDGOAL-1)	426483385	24533803	17.38	<.0001*
WS_number	-21229495	1258605	-16.87	<.0001*
(UNITPRICE-1)*(RBS_RDGOAL-1)	127866390	22324378	5.73	<.0001*
(WHSL_DELAY-1)*(MRF-1)	85195364	21665967	3.93	<.0001*
(UNITPRICE-1)*(WAR_FHRS-1)	83631789	22221761	3.76	0.0002*
(WAR_FHRS-1)*(RBS_RDGOAL-1)	78787654	21801368	3.61	0.0003*
(HP_OST-1)*(MTTR-1)	-78793428	22774336	-3.46	0.0006*
(MRF-1)*(WAR_FHRS-1)	71120002	22078089	3.22	0.0014*
(MRF-1)*(RBS_RDGOAL-1)	64920129	21811159	2.98	0.0031*
(UNITPRICE-1)*(MRF-1)	58819667	22248865	2.64	0.0085*
(MRF-1)*(MTTR-1)	55267739	21347489	2.59	0.0099*
MTTR	941670.29	1265034	0.74	0.4570

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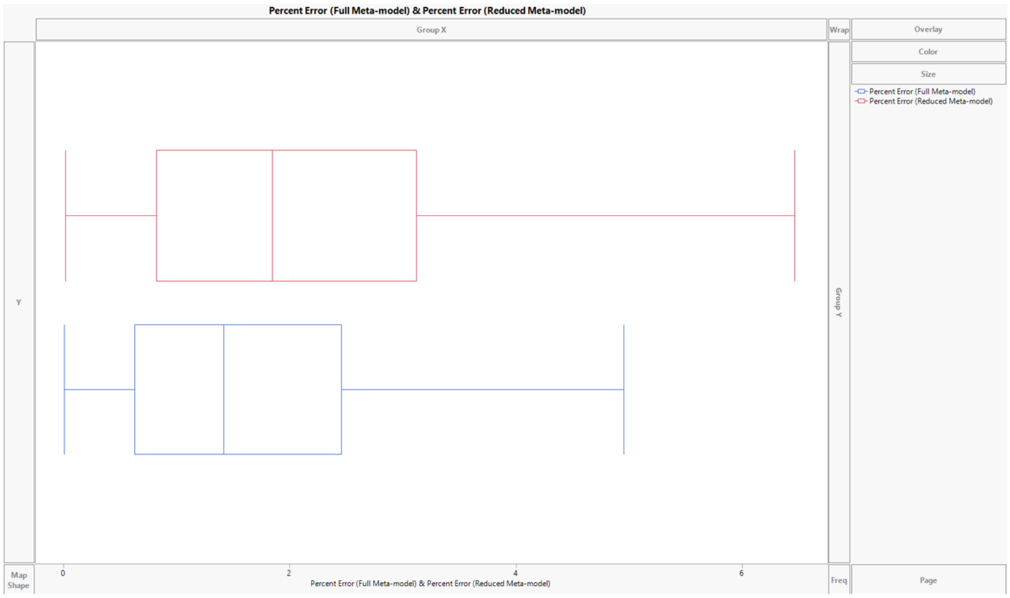
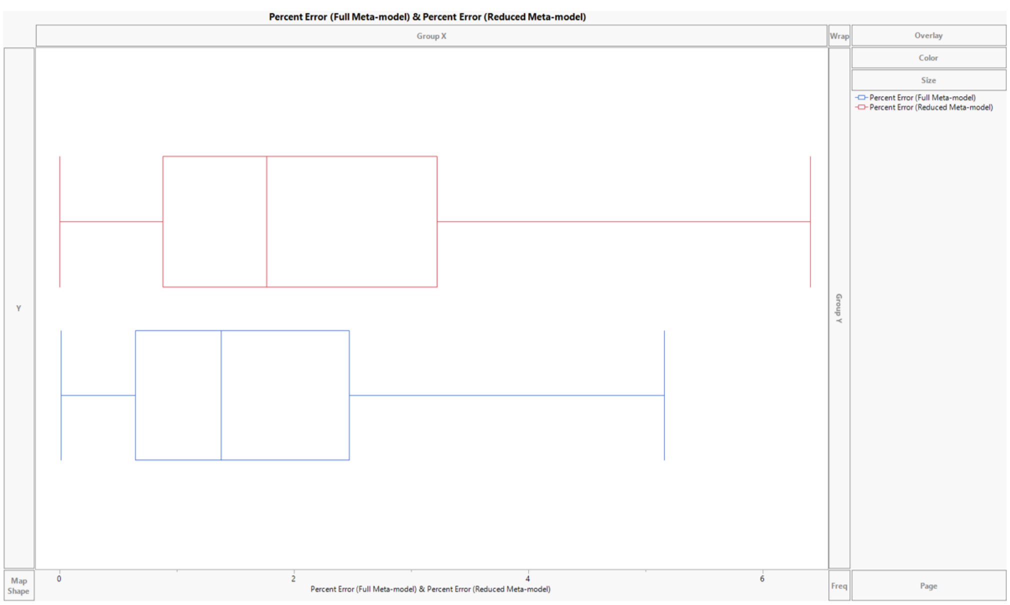
APPENDIX E. FULL AND REDUCED META-MODEL ERROR

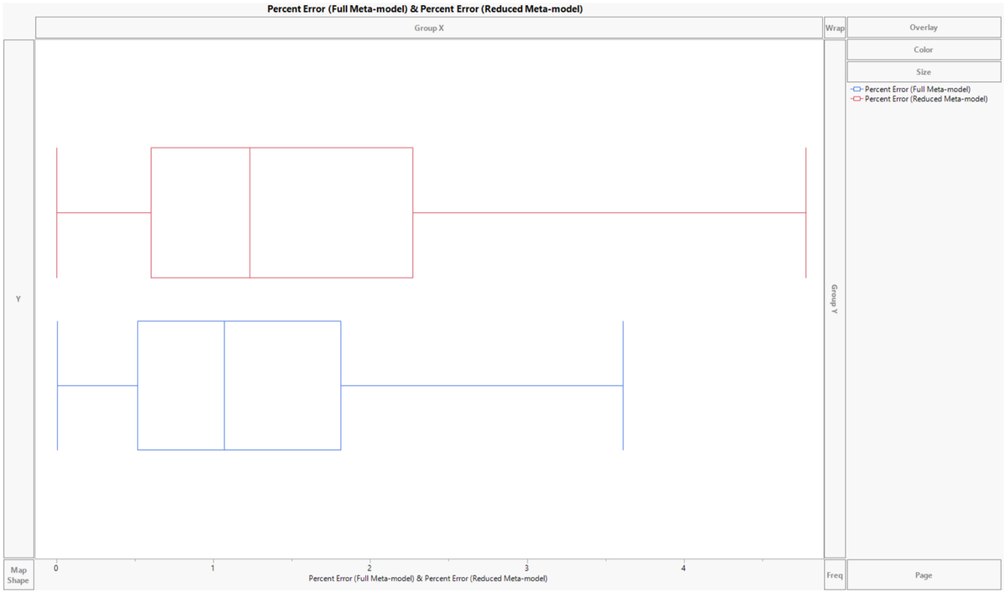
A. LEM FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



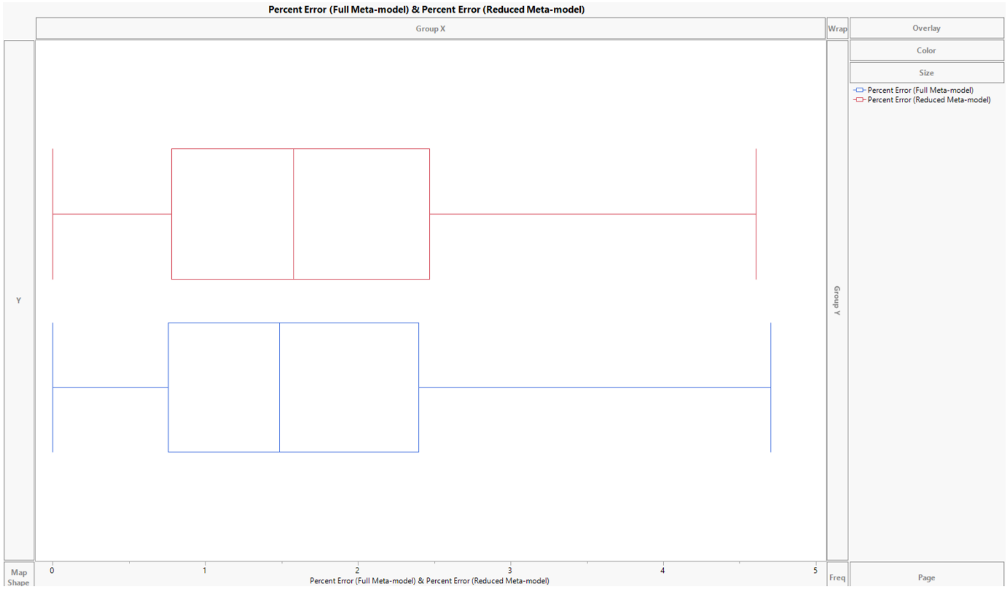
B. BAT FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



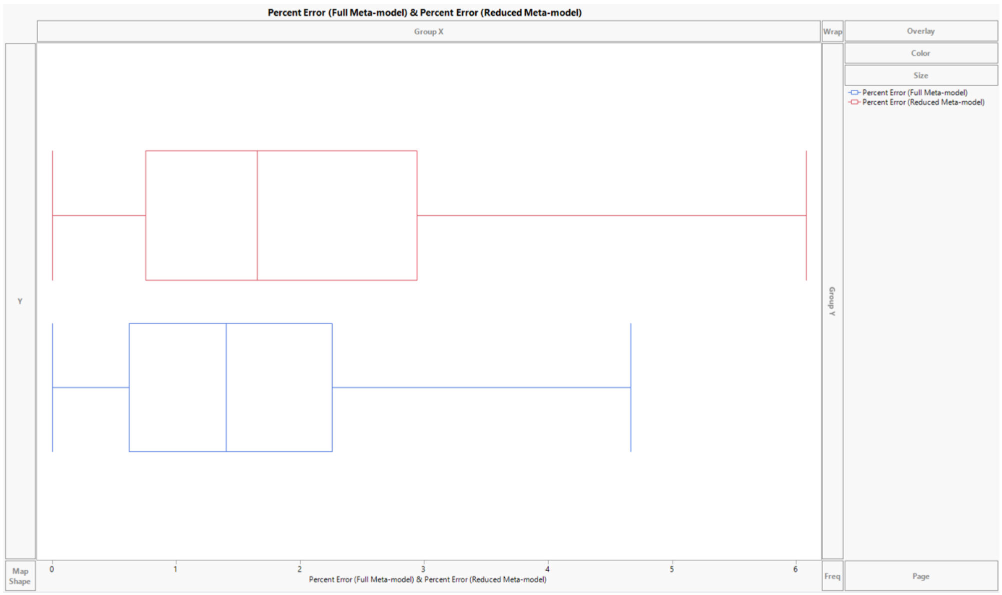
C. BON FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



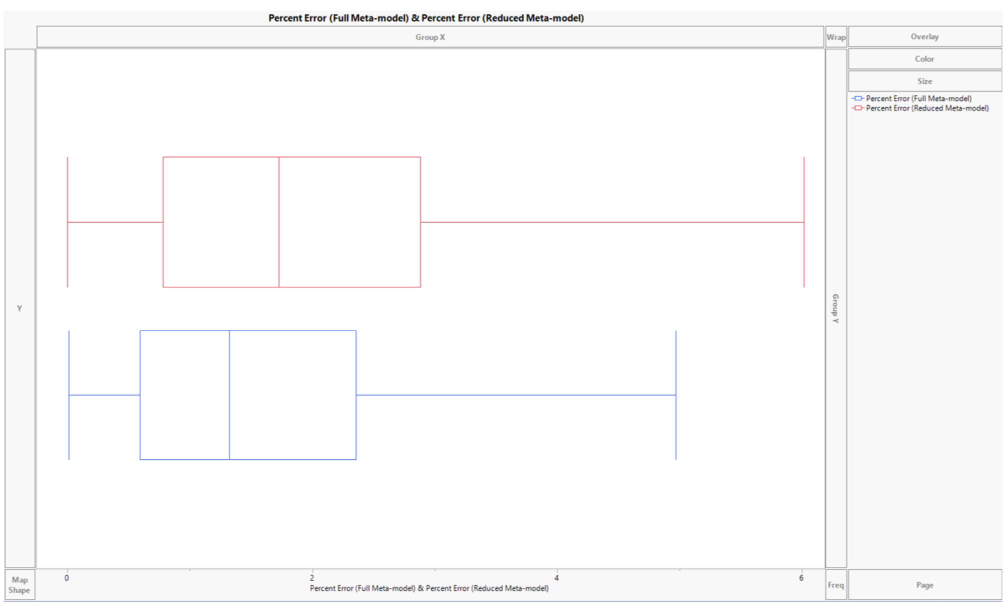
D. NOR FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



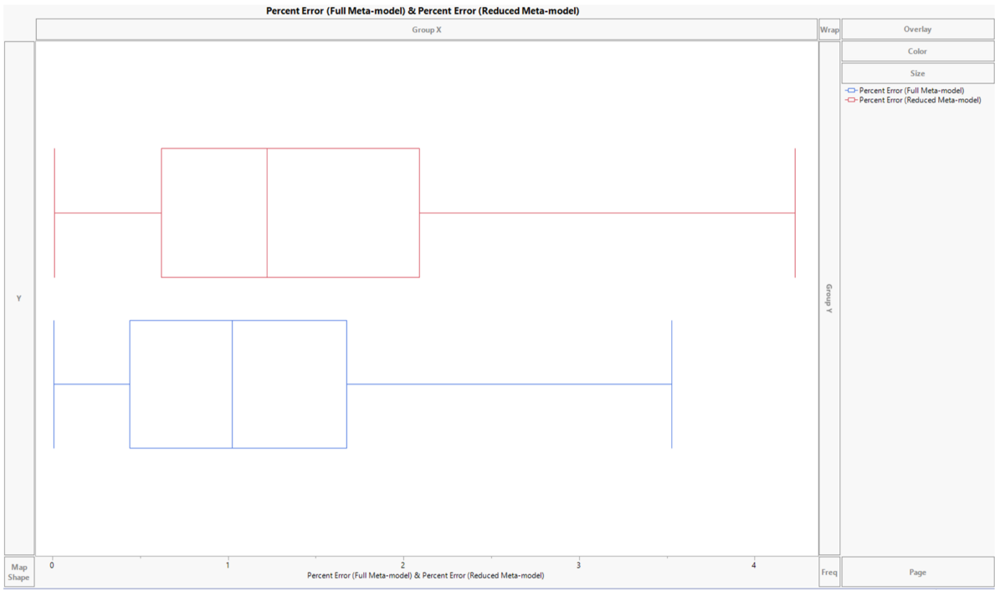
E. MAL FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



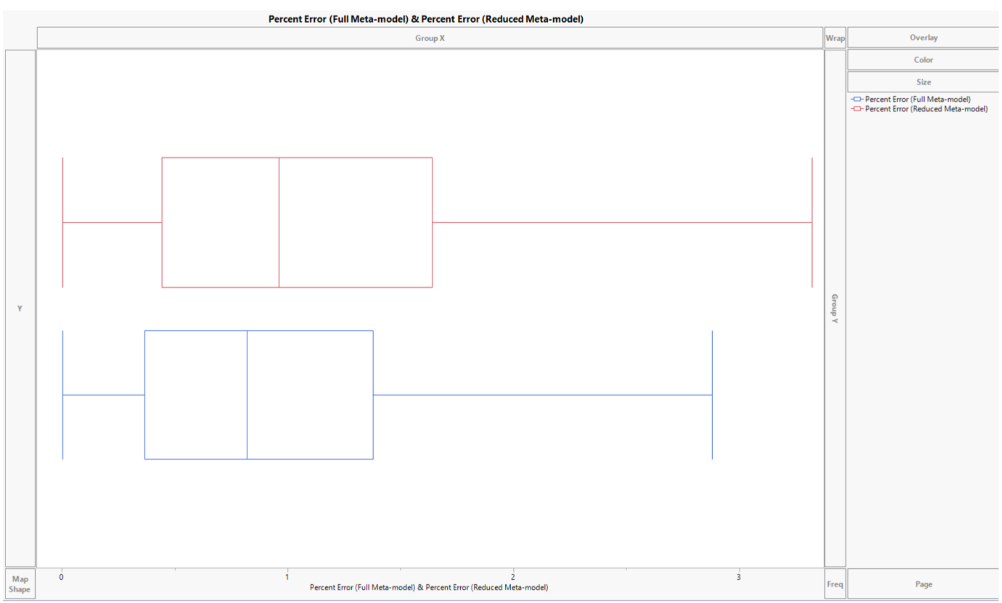
F. IWO FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



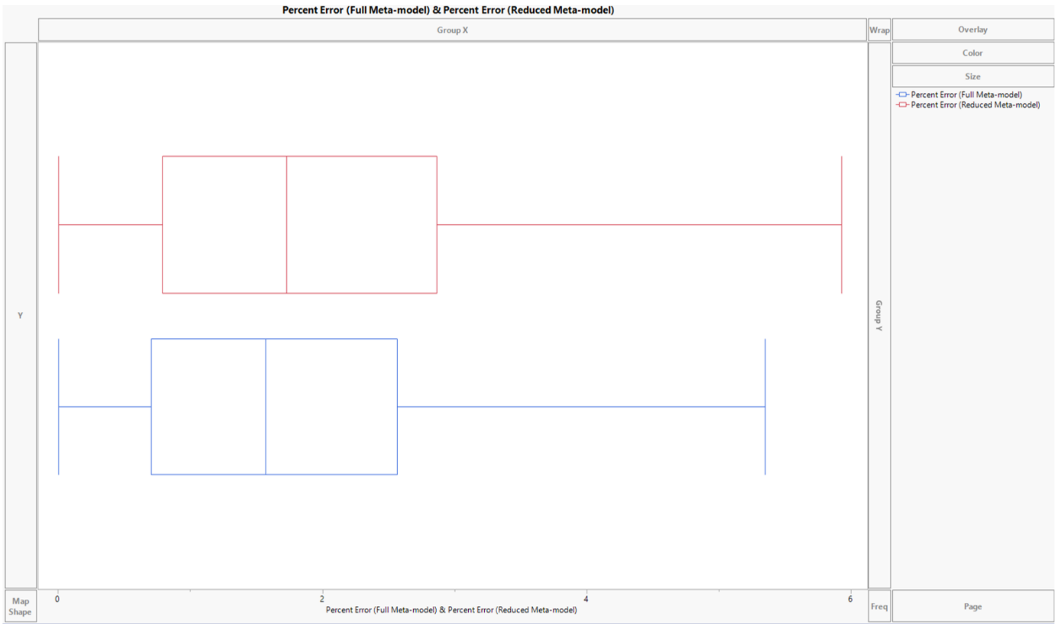
G. MIS FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



H. OCA FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



I. DEN FULL VERSUS REDUCED META-MODEL PREDICTION ERROR



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